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SPECTRAL ANALYSIS OF AMBIENT WEATHER PATTERNS

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SPECTRAL ANALYSIS OF AMBIENT WEATHER PATTERNS

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ABSTRACT

A Fourier spectral analysis of ambient weather data, consisting of global and direct solar radiation, dry and wet bulb temperatures, and wind speed, is given. By analyzing the heating and cooling seasons independently, seasonal variations are isolated and a cleaner spectrum emerges. This represents an improvement over previous work in this area, in which data for the entire year were analyzed together.

As a demonstration of the efficacy of this method, synthetic data constructed with a small number of parameters are used in typical simulations, and the results are compared with those obtained with the original data.

A spectral characterization of fluctuations around the moving average is given, and the changes in the fluctuation from season to season are examined.

NOMENCLATURE

A value of some meteorological variable

C cosine coefficient in Fourier series

N number of data points

P magnitude of the power spectrum

Q cumulative power spectrum

R autocovariance function

S sine coefficient in Fourier series

SUBSCRIPTS

r frequency

k time

INTRODUCTION

The energy performance of buildings, especially those with passive features, is strongly influenced by ambient weather conditions. This, in turn, makes the driving meteorological data an extremely important part of any energy analysis program.

Meteorological data is interesting because, while it contains very regular and well-defined patterns, it also contains stochastic elements. Anand, Deif, Bazques, and Allen (1), for example, used a simple sinusoidal trend combined with a joint probability matrix to characterize dry bulb temperatures and solar radiation values. On the other hand, Brinkworth (2) has reconstructed daily average insolation values using stochastically determined fluctuations superimposed on a linear moving average. Cumali (3) uses Fourier analysis on a monthly basis along with filtering techniques to identify cross correlations between several meteorological variables as a function of frequency range.

Hittle (4) concentrated on reproducing hourly data to an accuracy adequate for building energy analysis with as few Fourier coefficients as possible. After finding Fourier coefficients for a full year of data, he used the power spectrum to pick out one set of dominant frequencies to approximate the moving average, and another set of subdominant frequencies to approximate fluctuations. A more detailed comparison of this work with our study is given in the third section.

In this study, the Fourier analysis of ambient weather data is used to identify and characterize both the fundamental patterns (that is, the moving average) and the fluctuations about these patterns. Since both the moving average and the fluctuations have qualitatively different features in different seasons, the spectral analysis is done individually for four seasons through the year. The techniques used to do this are explained in the second section. In the third section, the results of the analysis are presented, and the conclusions are summarized in the fourth section.

ANALYSIS TECHNIQUE

Given a time series of data points A_k, $k = 0, 1, \ldots, N-1$, (for example, hourly dry bulb temperatures) a standard method of analysis is to use discrete Fourier transforms (5,6,7). Discrete Fourier transforms can be computed using Fast Fourier transform algorithms that are readily available (8). The discrete Fourier sine and cosine transforms are defined as:

$$S_r = 2 \sum_{k=o}^{N-1} A_k \sin \frac{2\pi kr}{N} \qquad (1)$$

$$C_r = 2 \sum_{k=o}^{N-1} A_k \cos \frac{2\pi kr}{N} \qquad (2)$$

where S_r and C_r are the sine and cosine transforms at some frequency r. The amplitude of sinusoidal variations (the magnitude of the power spectrum) at that frequency is given by

$$P_r = \left(C_r^2 + S_r^2\right)^{1/2} \qquad (3)$$

The time profile of any meteorological variable--for example, dry bulb temperatures--can be looked upon as the sum of two components: a moving average and a random fluctuation about this moving average. Correspondingly, in the frequency domain, one can also look upon C_r and S_r as consisting of two components. While it is not easy to readily identify the moving average component in either domain, it seems reasonable to expect that the magnitude of P_r will be large for at least the annual mean (r = 0 cycle/year), the annual seasonal cycle (r = 1 cycle/year), and the diurnal cycle (r = 365 cycles/year). Even though other frequencies are present in the moving average, it might be adequate for building energy analyses to restrict attention to these frequencies and their harmonics. Fluctuations could be imposed on this moving average by introducing additional frequencies chosen according to the magnitude of P_r. This is the approach taken by Hittle (4).

Both the moving average and the fluctuations around it have strong seasonal dependence. For example, the time of maximum and minimum daily temperatures varies seasonally. Therefore, it is desirable to do a Fourier spectral analysis seasonally rather than for the entire year.

As an example of the seasonal analysis method, let us consider one-fourth of a year centered around January 21. (This date was chosen since the average daily dry bulb temperature minimum occurs around this time of the year). The precise choice of a segment to represent a particular season is not critical). One cannot simply set N = 2190 (8760/4) and use Eqs. (1) and (2). The reason is that Eqs. (1) and (2) implicitly assume periodicity of temperature time series with a period N, which is not valid for N ≠ 8760. Instead, the following procedure was used. Suppose we want to represent the moving average in terms of a small set of frequencies, for example 0,1,2,365 cycles per year. Let the moving average be given by

$$\bar{A}_k = \frac{C_0}{2N} + \frac{1}{N} \sum_{r=1,2,365} C_r \cos \frac{2\pi kr}{8760} + S_r \sin \frac{2\pi kr}{8760}, \qquad k=0,1,\ldots,N-1 \qquad (4)$$

where C_r and S_r are quantities to be determined. Now choose C_r and S_r such that the mean square deviation

$$\frac{1}{N} \sum_{k=0}^{N-1} (A_k - \bar{A}_k)^2 \qquad (5)$$

is minimized.

If N = 8760, it is easy to show that this reproduces the Fourier coefficients as given by Eqs. (1) and (2). For any other value of N, the above procedure gives the best fit in terms of the chosen frequencies--in this case, constant, diurnal, annual, and semiannual cycles.

Having found the "best" moving average, as explained above, the fluctuations are obtained by subtracting the moving average from the original data. The resulting fluctuations can now be analyzed in the usual manner, using Eqs. (1) and (2) with N = 2190. The following relationships exist between P_r^2 and the root-mean-squared deviation from the moving average and the autocovariance function:

$$\frac{1}{N} \sum_{k=0}^{N-1} A_k^2 = \frac{1}{4N^2} \left[P_0^2 + 2 \sum_{r=1}^{N/2-1} P_r^2 + P_{N/2}^2\right], \qquad (6)$$

where the left side represents the mean-squared deviation. If the autocovariance coefficient R for some time k is defined as

$$R_k = \frac{1}{N} \sum_{k'=0}^{N-1} A_{k'} A_{k'+k} \qquad (7)$$

then it is related to the P_r^2 terms by

$$R_k = \frac{1}{4N^2} \left[P_0^2 + 2 \sum_{r=1}^{N/2-1} P_r^2 \cos \frac{2\pi kr}{N} + (-1)^k P_{N/2}^2\right], \quad k = 0,1,\ldots N-1 . \qquad (8)$$

The quantity P_r^2 as a function of the frequency r is usually referred to as the power spectrum. A useful quantity to characterize the fluctuations is the cumulative power spectrum (CPS), Q_r, defined by

$$Q_r = \frac{1}{4N^2}\left[P_0^2 + 2\sum_{r'=1}^{r} P_{r'}^2\right], \quad r = 0,1,\ldots N/2-1. \qquad (9)$$

With this definition of Q_r and the assumption that $P_{N/2}$ is small, the mean-squared deviation is given by the value of Q at N/2.

RESULTS

The methods described in the previous section were used to determine the moving average and the fluctuations in terms of a small set of frequencies on a full year as well as a seasonal basis. The Madison and Albuquerque Typical Meteorological Years (TMY) were used as the original data bases. Five different meteorological variables were chosen. They were direct normal radiation, global horizontal radiation, dry bulb temperature, wet bulb temperature, and wind speed. Of these five variables, primary emphasis was placed on the global horizontal radiation and the dry bulb temperature.

After a certain amount of experimentation, it was decided that frequencies 0,1,2,365 and 730 cycles/year provided a reasonable representation of the moving average for temperature variables and the wind speed. The role of the 0,1 and 365 cycles/year terms is obvious. The remaining frequencies, 2 and 730 cycles/year, account for the deviations of the annual and diurnal cycles from pure sinusoids. The radiation terms additionally required 1095 cycles/year (third harmonic of the diurnal cycle) to reasonably reproduce the abrupt on-off nature of sunrise and sunset.

Comparisons of the monthly average daily values for global horizontal and direct normal radiation for the three weather sets are shown in Figs. 1 and 2, while Fig. 3 shows the monthly average dry bulb temperature. The seasonally calculated values track the original TMY data quite well[1], while the full-year calculated values tend to distribute the radiation more evenly throughout the year. Figure 4 shows a comparison of the monthly heating degree-days. Both the full year and the seasonally calculated values agree quite well with the original data in the coldest months of the year and predict too few heating days in the warmer months. This is to be expected since the winter ambient temperatures in Madison are cold enough that the heating degree-days are essentially determined by the monthly average, which presumably is well represented by both of the calculated moving averages. On the other hand, heating degree-days in the summer are largely a function of peak or once-in-a-while events, which were necessarily ignored by the moving averages.

[1]Note that the seasonally calculated values even track the "kink" displayed by the TMY radiation data in Fig. 2.

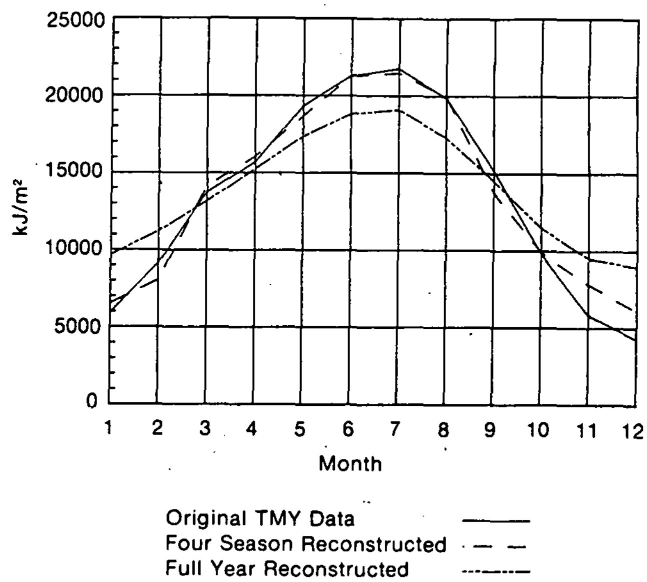

Figure 1. Average Daily Global Horizontal Radiation (Madison, TMY and Reconstructed)

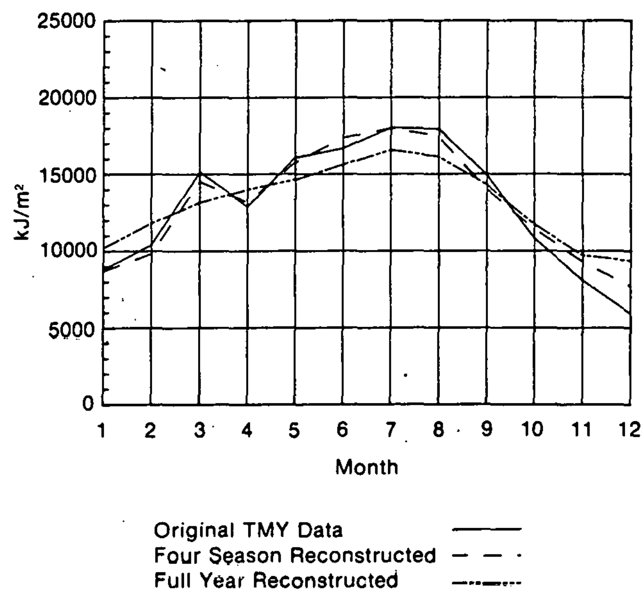

Figure 2. Average Daily Direct Normal Radiation (Madison, TMY and Reconstructed)

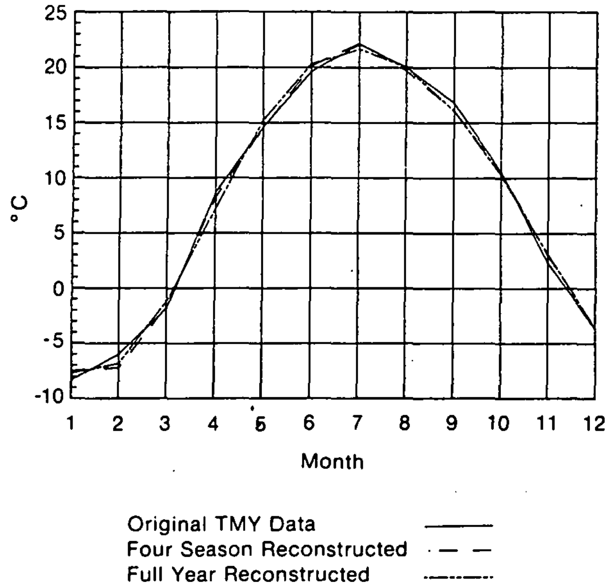

Figure 3. Average Daily Dry Bulb Temperature (°C) (Madison, TMY and Reconstructed)

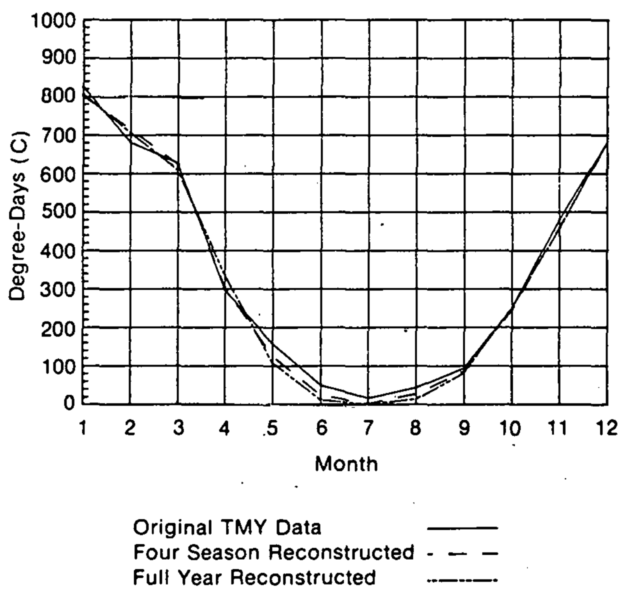

Figure 4. Monthly Heating Degree Days (18.3°C Base) (Madison, TMY and Reconstructed)

The second component of the overall weather profile is deviation about the moving average. Figure 5 shows the cumulative power spectrum (CPS) for deviations around the dry bulb temperatures in Albuquerque. The full-year calculated values shown here are actually the seasonal sums of the deviations that arose from an annually calculated average. Thus it is possible to compare the magnitude of the deviations from the two reconstructed techniques directly on a seasonal basis. For the sake of clarity, only the winter (approximately Dec. 6 to Mar. 7) and summer (approximately June 6 to Sept. 6) curves are shown (the curves for both of the swing seasons lie between these curves).

The annually calculated CPS values indicate mean deviations of about 4.5° and 3.1°C for winter and summer respectively. These values are larger than the seasonally calculated values, which show mean deviations of about 4.0° and 3.0°C. Overall, the winter values are much larger than the summer values, and there is a difference between the annually and seasonally calculated values. This indicates that winter temperatures in Albuquerque tend to be much less regular and more random than those in the summer.

It is interesting to compare Fig. 6, the CPS curves for global horizontal radiation, with Fig. 5. In Fig. 6, deviations for both of the annually calculated curves (452 and 477 kJ/m^2-hr) for winter and summer, respectively) are much higher than for the seasonally calculated curves (299 and 385 kJ/m^2-hr), again demonstrating the importance of

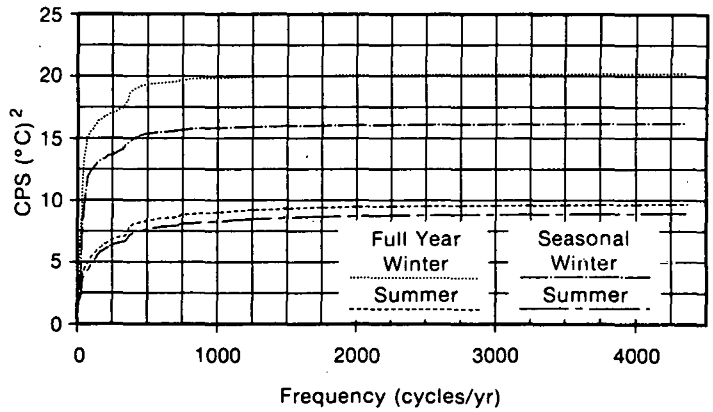

Figure 5. Cumulative Power Spectrum: Dry Bulb Temperature (Comparison of Full Year with Seasonal Calculations; Albuquerque)

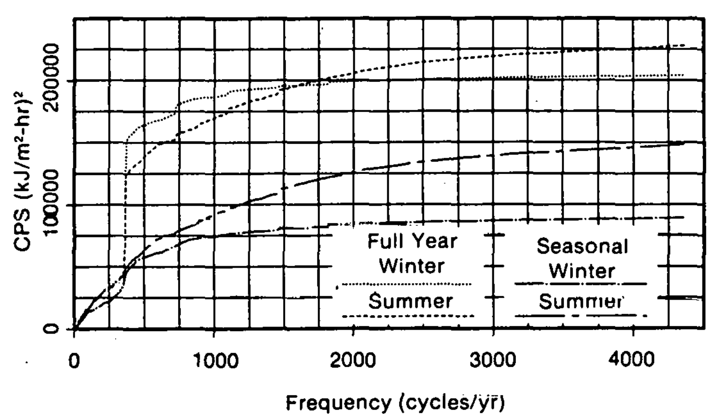

Figure 6. Cumulative Power Spectrum: Global Horizontal Radiation (Comparison of Full Year with Seasonal Calculations; Albuquerque)

seasonal analysis for radiation values. Another interesting observation is the notable difference in the shapes of the radiation curves in Fig. 6 as compared to the temperature curves in Fig. 5. While the temperature curves have a very high slope at low frequencies and then tend to level out, the radiation curves tend to maintain a much more constant value for the slope, particularly in the summer seasons. This indicates that higher-frequency deviations are substantially more important in the radiation values, and is partly a relic of the fact that the radiation turns on and off so abruptly.

All of the curves on these graphs have significant abrupt increases at about 365 cycles/year and several of its harmonics. In fact, the annually calculated radiation CPS curve is dominated by a few large coefficients near 365 cycles/year. (Remember that the 365 cycles/year term was explicitly included in the moving average for the radiation and therefore does not contribute to the CPS.) This occurs because the moving average is not adequately described by the 365 cycles/year term over an entire season (and even less adequately over an entire year). Particularly for radiation values, the 364 and 366 cycles/year coefficients are significantly larger than those around them. This fact has also been noted by Hittle (4), who ascribes it to phenomena like variations in day length and variations in the time of daily extrema[2]. Since these variations are less pronounced within a season, there is a marked decrease in the prominence of the 365 cycles/year region in the seasonally calculated values of Fig. 6.

In order to illustrate the role of the moving averages and the fluctuations in building energy analysis, building simulations were run on DOE-2 (9) with 3 sets of data: the original Madison TMY data, the seasonally generated moving average data, and the full year generated moving average data. The building model used in these simulations was a 41.8-m^2 shoe-box structure with a long east-west axis. The south wall consisted primarily of a 27.4-m^2 double-glazed window, which was managed with 0.81 W/m^2-°C (R-7) night insulation through the winter. The walls and roof were a 0.57 W/m^2-°C (R-10) composite weighing about 366 kg/m^2. The thermostat setting was 20°C during the day, with a night set-back to 15.6°C.

The results shown in Fig. 7 for monthly loads not met by solar are easily explained in terms of the information on Figs. 1 through 4 and the fact that the building used is so highly solar driven. The heating loads predicted by the three weather sets agree reasonably well in the swing months, but the reconstructed data sets predict too small a load in the cold months. For example, the loads predicted by the original data in November are almost twice as large as predicted by either of the reconstructed weather sets. This is caused by the fact that while the ambient temperatures (and number of degree-days) on the three sets are very close, the two reconstructed sets have as much as 1.5 times more insolation. Since the building is so highly solar driven, the heating load seen by the plant is significantly smaller.

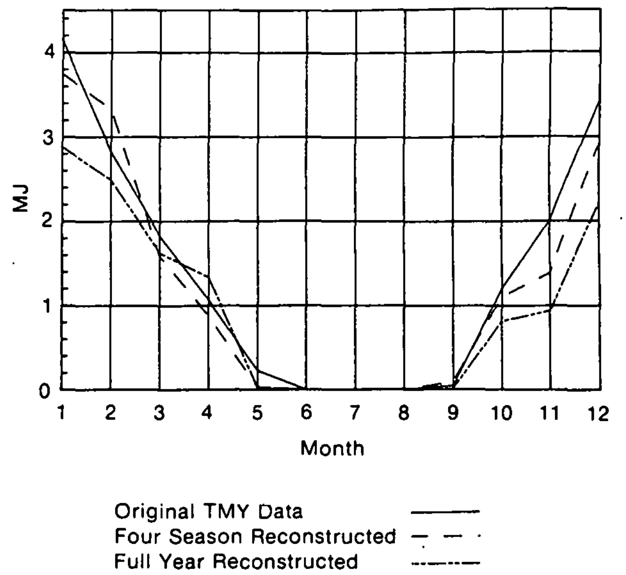

Figure 7. Monthly Loads (Madison, TMY and Reconstructed)

The agreement between the annually calculated data and the original data is probably the worst in January and February, where the loads differ by as much as 30%. The worst differences for the seasonally calculated values are also in the winter months, where they reach 16%. The magnitude of the differences demonstrated here is similar to that found by Hittle (4), who reported differences in monthly values as high as 20-30% even though the building he simulated was a commercial structure that was probably less sensitive to ambient conditions.

Figures 8 and 9 demonstrate another inadequacy of simply using the moving average. Figure 8 shows

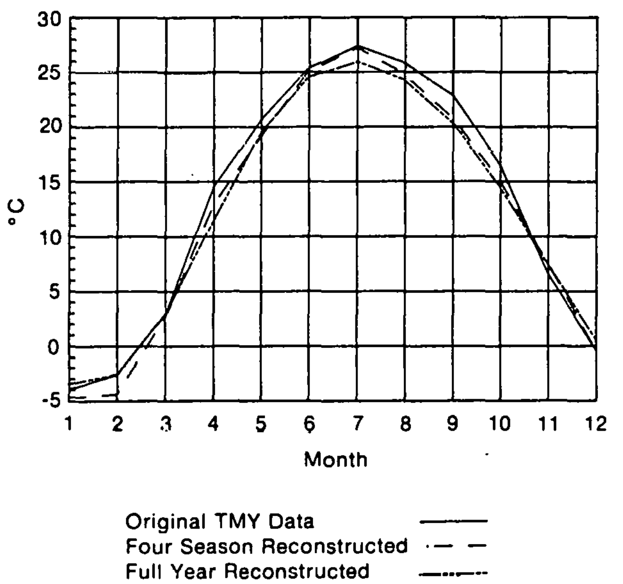

Figure 8. Average Daily Maximum Dry Bulb Temperature (Madison, TMY and Reconstructed)

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[2]He additionally attributes it to the fact that a year is actually 365 1/4 days.

a comparison of the monthly average daily maximum dry bulb temperatures. Since the reconstructed data sets have necessarily eliminated extremes, they always show lower maximums in the warmer months and very similar maximum values in the winter months. Figure 9 shows vividly how the moving average data fails to accurately predict mechanisms that are driven by peak events. In this case, the monthly maximum zone temperatures are plotted. While the reconstructed data predict almost the same maximum values in the warmest and coldest months, they always predict too little overheating in the swing seasons.

Overall, the moving average tends to predict average and long-term values well, while predicting peak events rather poorly. In addition, the seasonally calculated moving average values provide a better estimate of temperatures and a much better estimate of radiation values than the annually calculated values.

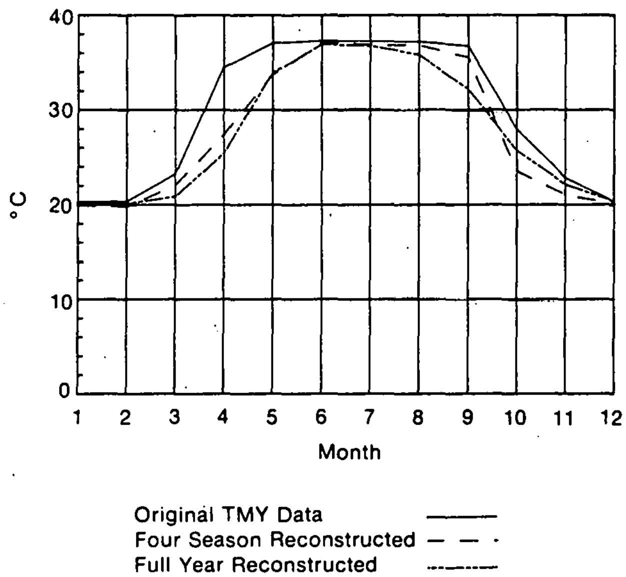

Figure 9. Monthly Maximum Zone Temperatures (Madison, TMY and Reconstructed)

CONCLUSIONS

The major conclusions that arise from this work are the following:

- Fourier analysis of meteorological variables, on a seasonal as opposed to an annual basis, provides a significantly better characterization of important patterns and minimizes several undesirable trends in deviations about the moving averages. This is particularly true of the radiation variables.
- The moving average values provided by reconstruction of hourly data from just a few Fourier coefficients can be useful for "quick and dirty" analysis of buildings which are not highly solar driven. However, more accuracy is needed to successfully reproduce the behavior of buildings that are more responsive to environmental factors.
- The cumulative power spectrum is a useful method for characterizing the deviations about the moving average, and provides a significant amount of information about how well the particular variable is described by the moving average.

Further work in this area should include more exploration into the properties of the moving average as it relates to building energy use, and refinement of the method of characterizing and regenerating the deviations. Particular attention should be paid to the importance of cross-correlation between variables in the deviations. In addition, an exciting prospect for this type of analysis is its potential for analyzing peak events, (e.g., overheating) without necessitating the simulation of performance over an entire year. This area needs further exploration. In general, this technique of characterizing weather data has great promise in at least three major areas of interest to building energy analysis:

- brief characterization of meteorological data. This could be especially useful for energy analysis on mini- or microcomputers.
- generation of hourly data for locations where only average data is available. Given that moving average data can be constructed from relatively little information, fluctuations about the moving average could be taken from a nearby site and full hourly weather data files could be generated.
- better understanding of the meaning of typicality in long-term data. A technique very similar to this was originally considered for the generation of the Typical Meteorological Years (10). A truly major advantage of a technique like this is that it is not necessary to assume that one of the available months will be "typical enough" to represent the long term.

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