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PREDICTING DYNAMIC BEHAVIOR OF A PASSIVE HOUSE USING PERFORMANCE DATA

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1. Introduction

In the search for improved design methods it is valuable to be able to use a few simple parameters to describe a building's thermal performance. The average performance of a building can be described adequately using steady-state heat-loss coefficients, which can be estimated from performance data (1). Dynamic performance data have been used by Subbarao (2) to estimate transfer functions which describe instantaneous thermal behavior. Our treatment is similar to Subbarao's in that we operate on the Fourier Transforms of temperature and insolation time series to obtain transfer functions in the frequency domain.

However, in contrast to Subbarao's approach, which employs a four-day period to estimate parameters which are used to predict performance over a successive period of similar duration, we consider the potential for longer-term predictions. Our data set consists of measurements in two houses of different construction over 132 days. Since both houses were passively heated and since solar angles vary considerably over such a long period, it is necessary to include variable sunshading effects explicitly.

The eventual aim of the present line of inquiry is to be able to use a small data set to estimate transfer functions which can then be used to successfully predict long term dynamic performance. As a first step toward this goal, we use the entire data set to estimate transfer functions. We use these transfer functions to predict dynamic performance over the same period. A good fit between measurement and prediction indicates that the transfer function model adopted here is a good description of dynamic behavior. Further work will examine how to estimate the key parameters with greater economy of data.

We explain some of our terms and give an overview of the method in section 2.1. Section 2.2. describes the houses and the measurements. Section 2.3. discusses the shading problem in greater depth. Section 2.4. explains our estimation procedure very briefly. We are currently preparing a more thorough exposition of the method. Results are quoted in section 3. Conclusions and anticipated refinements to the method are outlined in section 4.

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2. Method

2.1. Explanation of terms

A building can be pictured as a weather filter. It modifies the fundamental signals air temperature and solar radiation to produce an internal temperature profile (which hopefully lies within acceptable limits). The methods we employ here resemble the tools electrical engineers use to study and design filters. Our aim is to deduce the filter characteristics of constructed buildings by analyzing the inputs (air temperature and insolation) and the output (internal temperature).

Thermal mass introduces time lags, making a representation of the filter in the time domain rather complicated. For convenience, we swap to the dual representation in the frequency domain. The transition from a time series representation of a time-dependent quantity to a frequency-domain representation is accomplished by the Fourier Transform. The inverse transition is accomplished by the Inverse Fourier Transform.

The transfer functions which we use to describe the filter characteristics are three complex functions of frequency. We estimate values for these functions at each frequency by solving a set of simultaneous linear equations. This least-squares estimation procedure is similar to standard multiple linear regression (3) with some important differences noted below.

2.2. Measurements

The two houses employed in this study form part of the Bonnyrigg Solar Village, situated in the western suburbs of Sydney, Australia. One is an insulated cavity brick house on a concrete slab. The other is an uninsulated timber house with a suspended timber floor. The monitoring system is described in detail and the construction of the houses is explained in (4). The masonry house is number 341 and the timber house is number 359 in that document.

The measurements employed here are internal temperatures for each house, ambient temperature, and insolation striking a North-facing vertical surface (since this is a Southern Hemisphere study). Hourly values obtained between March and July 1982 were used to construct sixty-six periods of forty-eight hours duration each.

For the most part, no heating or cooling appliances were used between March and July. However, there were a number of brief bursts of heating and air conditioning. Periodically, doors and windows were opened (although never overnight). Towards the end of the study, carpet was placed in the masonry house and the windows in the timber house were covered with aluminium foil. The data have not yet been screened for events of this sort.

2.3. Shading

The relationship between ambient insolation and solar energy

penetrating the house is not constant from month to month or even from hour to hour during the day because fixed overhangs and other shading devices exclude the sunlight in a highly time-dependent way.

The regression technique is not flexible enough to account for these complexities so we chose to estimate transfer functions relating the insolation admitted by shading devices, or shade-adjusted insolation, to internal temperature. We expect this relationship to be fairly linear and fairly time-independent.

Although we did not measure shade-adjusted insolation and it is not an easy quantity to measure, it can be calculated by taking into account the ambient insolation, the solar altitude and azimuth angles, and the geometry of the fixed sunshading devices. This calculation was performed prior to the least-squares estimation steps.

2.4. Estimating the transfer functions

2.4.1. Notation

Our data set consists of sixty-six periods of time, each forty-eight hours long. For each of these periods, we have three discrete time-series; I_{tk} being the indoor dry bulb temperature (for the house in question), A_{tk} being the ambient dry-bulb temperature, and Q_{tk} being the shade-adjusted insolation in Watts per metre squared. The subscript k refers to the period (1 to 66) and the subscript t refers to the hour (0 to 47) within the period.

Taking the Fourier Transform of each of these time series, we obtain the following complex transforms: II_{fk} for indoor temperature, AA_{fk} for ambient temperature, and QQ_{fk} for shade-adjusted insolation. Once again, the subscript k refers to the period (1 to 66). The subscript f refers to the frequency (0 to 24) in cycles per period. Generally, we shall denote the Fourier Transform of a time series T by doubling the letter; TT.

In the interest of making the equations as general as possible, we shall refer to the number of periods, 66, as M, and the number of hours per period, 48, as N.

2.4.2. Least-squares estimation

We construct a linear function of the fundamental signals ambient temperature and shaded insolation:

$$RR_{fk} (a_f, b_f, c_f) = a_f + b_f QQ_{fk} + c_f AA_{fk} \qquad (1)$$

RR_{fk} depends upon the complex values a_f, b_f, and c_f. RR_{fk} is the Fourier Transform of a time series R_{tk}, which likewise depends upon a_f, b_f, and c_f.

We seek the complex values for a_f, b_f, and c_f which will minimize the root mean square deviation between R_{tk} and I_{tk} over all hours, t, and all periods, k. These values will be the least-squares estimates of the transfer functions relating indoor temperature to ambient temperature and shaded insolation.

The process of estimating values which minimize the root mean square deviation is analagous to multiple linear regression, however here it is complicated since we are estimating coefficients in the frequency domain which minimize deviations in the time domain.

Introducing the error function, $E_{tk} = R_{tk} - I_{tk}$, its Fourier Transform, EE_{fk}, and e, the sum of E^2_{tk} over all t and k, we note that the first order conditions for minimization of e are :

$$de / da_f = 0, \quad de / db_f = 0, \quad de / dc_f = 0 \quad (2)$$

For f = 0, these conditions imply:

$$\sum_{k=1}^{m} EE_{0k} = 0 \ , \quad \sum_{k=1}^{m} QQ_{0k}\ EE_{0k} = 0 \ , \quad \sum_{k=1}^{m} AA_{0k}\ EE_{0k} = 0 \quad (3),$$

as in multiple linear regression. However for f <> 0, the first order conditions imply:

$$\sum_{k=1}^{m} EE_{(N-f)k} = 0 \ , \quad \sum_{k=1}^{m} QQ_{fk}\ EE_{(N-f)k} = 0 \ , \quad \sum_{k=1}^{m} AA_{fk}\ EE_{(N-f)k} = 0 \quad (4)$$

These equations differ from similar equations used in regression in that the subscript of EE is (N-f) rather than f. This subtle difference arises because we are attempting to minimize root mean square deviation in the time domain rather than the frequency domain.

Equations (3) can be used to construct a 3x3 regression matrix which is then inverted to obtain the real components of a_0, b_0, and c_0. Equations (4) can be used to construct a 6x6 matrix for each nonzero frequency, f, which is inverted to obtain the real and imaginary components of a_f, b_f, and c_f.

2.4.3. Evaluating the estimates

Having obtained a complete set of complex coefficients a_f, b_f, and c_f, it is possible to construct the function RR_{fk}, using equation (1). Taking the Inverse Fourier Transform of RR_{fk}, we obtain the time series R_{tk}, which is comparable to I_{tk}. To simplify the comparison of the constructed time series, R_{tk}, to the measured time series, I_{tk}, we renumber the indices of each so that they become simple vectors R and I, each containing NxM elements.

By way of comparison, we subtract each element of R from the corresponding element of I and take the mean and standard deviation of the resulting difference vector. We also calculate the simple correlation coefficient between I and R.

Fig.1. Timber house. Measured minus constructed time series.

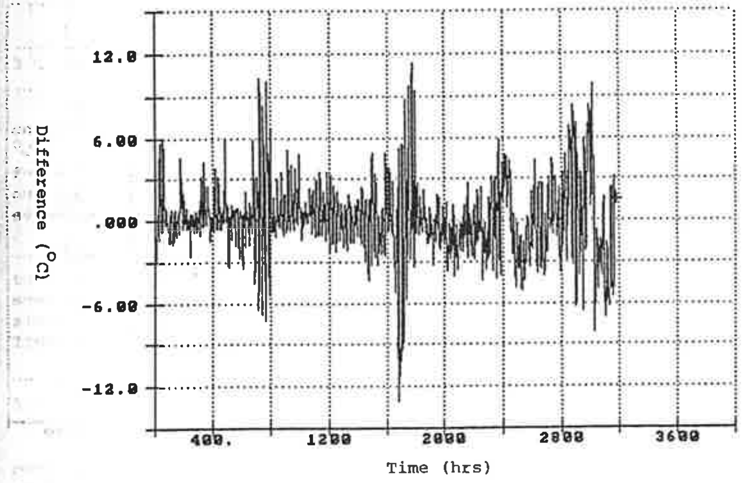


Fig.2. Timber house. Plot of constructed versus measured temperatures. Each point is one hourly value.

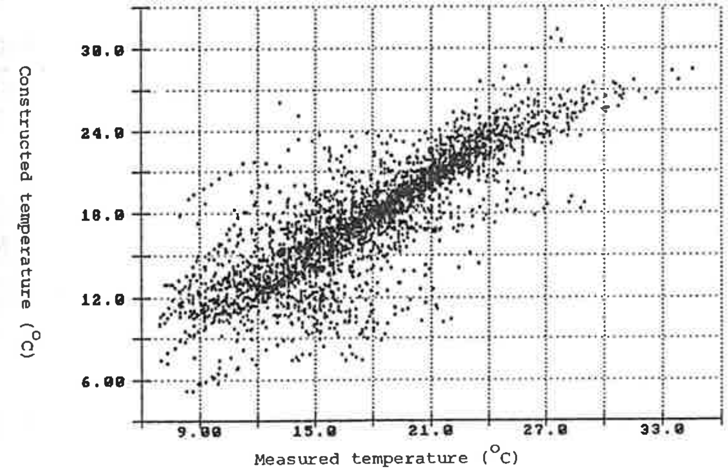


Fig.3. Masonry house. Measured minus constructed time series.

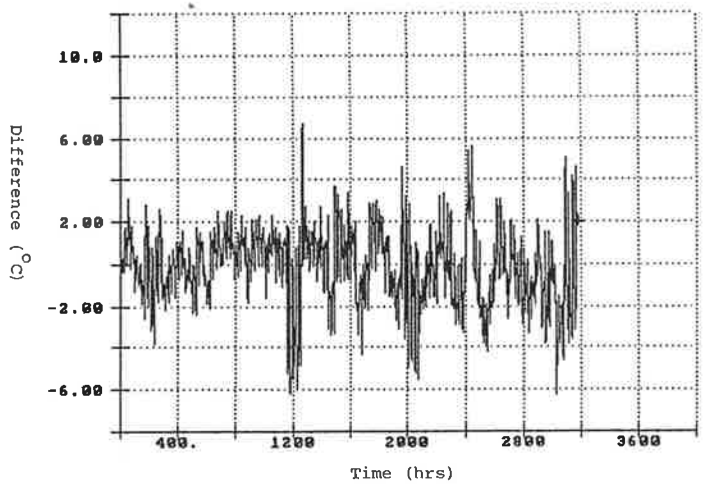
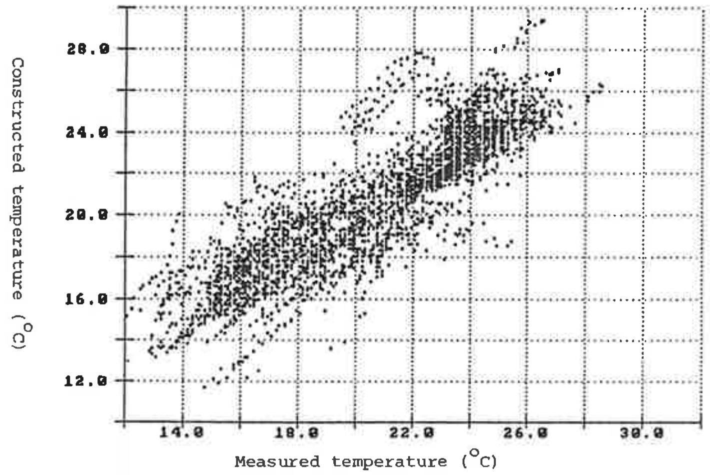


Fig.4. Masonry house. Plot of constructed versus measured temperatures. Each point is one hourly value.



3. Results

3.1. Timber house

Figure (1) illustrates the difference between the measured and constructed time series for the timber house. The mean difference is 0.0 °C and the root mean square difference is 2.6 °C. Clearly if it weren't for the two concentrated bursts of deviation near hour 750 and hour 1700 and the deviating section after hour 2800, the standard deviation would be significantly lower.

Figure (2) is a plot of measured temperature versus constructed temperature. Each dot represents one hourly measurement. Despite some scattering, the densest clustering of points clearly follows a line with slope of unity and a zero intercept. This qualitative observation of linearity is confirmed by a correlation coefficient of 0.85 .

3.2. Masonry house

Figure (3) illustrates the difference between the measured and constructed time series for the masonry house. The mean difference is -0.2 °C and the root mean square difference is 1.7 °C. Figure (4) is a plot of measured versus constructed temperature. Once again, the evident linear trend is supported by a correlation coefficient of 0.87 .

4. Conclusions and further work

Empirical data are needed to make wise decisions in building energy management. When such data are available, they are often used in a highly condensed form (such as monthly averages) which fails to provide much insight into dynamic behavior. We have illustrated a method of condensing empirical data which takes full account of dynamic features, but which does not suffer from a high degree of model or climate dependence.

In many respects, this study is preliminary. The data have not been screened for events which are likely to have had a spurious influence on the results. The estimation method itself is experimental. Two improvements would be a) using time series of longer than forty-eight hours duration to capture important low-frequency effects, and b) employing a smooth windowing function prior to the calculation of Fourier Transforms to avoid distorted peak heights.

The method presented here produces a good match between prediction and measurement. This agreement holds for buildings at both extremes of thermal mass, for hourly values over a several month period. As model validation studies have repeatedly shown, this kind of agreement is very difficult to acheive.

Possible uses for this method include model validation, a shorthand way to describe a building's dynamic features, simplifying design tools, and assessing energy use within a building. Primarily, though, it shortens the tedious and often vague cycle of design, construction, and evaluation by strengthening the link between measured performance and theoretical transfer functions.

5. References

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