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THE EFFECT OF SOLAR DATA ERRORS ON THE PERFORMANCE AND ECONOMICS OF SOLAR SYSTEMS

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THE EFFECT OF SOLAR DATA ERRORS ON THE PERFORMANCE AND ECONOMICS OF SOLAR SYSTEMS*

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1. INTRODUCTION

The needed accuracy of solar radiation data for application to solar energy systems has been a topic of interest for some time. The desired accuracy for, say, a solar data network is often expressed in terms of what is considered realizable given the available instruments, data handling methods, interpolation techniques, and the like. The designer of a solar energy conversion system, generally unfamiliar with the difficulties of data taking, would like the data to be (and will often use the data as though they were) error free. In neither case is the effect of the data errors on the design of solar systems given much attention.

We address this situation by presenting an analytical framework that relates the errors in solar data to their effect on calculations of the performance and economics of certain solar systems. The analysis applies to systems in which the performance is expressed as the fraction (the so-called solar fraction) of a specified energy load that is supplied by solar energy. A set of dimensionless parameters is presented that describes the sensitivity of the predicted performance and costs to errors in the solar radiation data. A simple, heuristic, model is used to illustrate the basic points of the analysis. A solar heating system for a building of conventional construction is taken as a more realistic case study.

This paper is based on a report by same authors (Grether et al., 1983) that derives the sensitivity parameters presented here. The reader is referred to this longer version for the mathematical details.

2. SOLAR SYSTEM PERFORMANCE

The type of solar energy system to be considered is one for which there is a specified annual energy load, E_L. The solar system will accept input energy in the form of solar radiation and produce some amount of usable output energy, E_s. A quantitative measure of the performance of the system is given by the solar fraction,

$$f_s = E_s/E_L. \quad (1)$$

The functional dependence of the solar fraction may be represented as

$$f_s = f_s(E_L, A, I, p_1, p_2, \ldots) \quad (2)$$

where A is the collector area, I the incident solar radiation, and p_1, p_2, ... any other parameters of the system.

The functional dependence for actual systems can be quite complicated. For purposes of illustration it proves useful to consider a Simple Heuristic Performance Model (SHPM) that is shorn of these complications. In general, when a solar system is designed to provide a small fraction of the load, then an increase in collector area will result in about the same percentage increase in the usable solar energy. However, for progressively larger solar fractions an increase in area will result in a progressively smaller percentage increase in the usable energy (i.e., one reaches the point of diminishing returns). The form chosen for the SHPM that satisfies these conditions is

$$f_s = 1 - \exp(-A/A_o). \quad (3)$$

As can be seen by setting $A = A_o$ in this equation, A_o is the collector area needed to provide 63.2% of the load. Eq. (3) is plotted in Fig. 1 as a function of A/A_o.

As a more realistic case we consider a solar space and water heating system for an otherwise conventional building. A number of design models are available that permit convenient calculation of the solar fraction in terms of the collector area, the incident solar radiation, storage capacity, flow rates, and the like. The model of Klein et al. (1976) as embodied in the computer code FCHART Version 3.0 (1978) was selected for the analysis. Hereafter the model will be referred to as FCHART.

FCHART uses average (typically, averaged over many years) monthly values of the solar radiation, ambient temperature, and degree days. FCHART computes (among other things) monthly and annual values for the solar fraction. FCHART was used to calculate the relationship between

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collector area and solar fraction for three climates: Madison, Wisconsin; Atlanta, Georgia; and Los Angeles, California. (See Grether et al., 1983 for details.) Fig. 1 displays the annual solar fraction vs A/A_o for the three cities. The values of A_o vary by a factor of seven from the mildest (Los Angeles) to the most severe (Madison) climate but, when plotted as in Fig. 1, the general trends are quite similiar for the three cities and the SHPM.

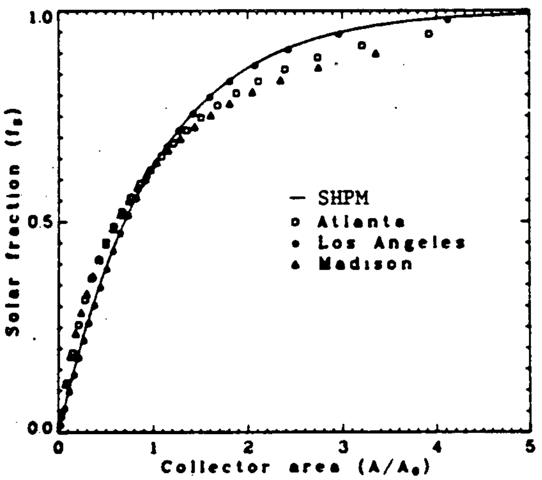

Fig. 1. *System performance vs. normalized collector area for the Simple Heuristic Performance Model (SHPM) and three climates.*

3. EFFECT ON PERFORMANCE OF SOLAR DATA ERRORS

Suppose that a design procedure such as FCHART is used to calculate f_s, but that the solar radiation data are in error by some amount. By means of a series expansion it can be shown (Grether et al., 1983) that

$$\delta f_s = \alpha \cdot \delta I \qquad (4)$$

where δI and δf_s are the fractional errors in the solar radiation and solar fraction respectively,

$$\delta f_s = \frac{[f_s(I_e) - f_s(I_a)]}{f_s(I_a)} \qquad \delta I = \frac{(I_e - I_a)}{I_a}$$

The subscript "a" refers to the actual value of solar radiation and "e" the erroneous value. α is the "sensitivity" of the solar fraction to solar data errors and is just

$$\alpha = \frac{I_a}{f_s(I_a)} \cdot \left(\frac{\partial f_s}{\partial I}\right)_a \qquad (5)$$

The SHPM can be generalized to incorporate the dependence on solar radiation by assuming that a percentage increase in the solar radiation incident on the collector surface is equivalent to the same percentage increase in collector area. The SHPM is then

$$f_s = 1 - \exp\left(\frac{-I_e}{I_a} \cdot \frac{A}{A_o}\right) \qquad (6)$$

where I is the radiation incident on the collector surface. This expression may be substituted into Eq. (5) with the result

$$\alpha = -\ln(1-f_s) \cdot (1-f_s)/f_s \qquad (7)$$

Note that α is only a function of the solar fraction, with no explicit dependence on a specific collector area or incident solar radiation value. The parameter α is plotted against the solar fraction in Fig. 2 for both the SHPM and the solar heating case.

Two comments with respect to FCHART are in order before examining Fig. 2 in detail. Firstly, the built-in solar radiation values of FCHART are certainly inaccurate to some extent and the actual values are, of course, unknown. However, for the purposes of this analysis the built-in values are taken as the actual (errorless) ones. There is a good justification for this approach. Suppose that the analysis is being done for Madison. We can define that the solar radiation values, while in error by some unknown amount for Madison itself, are characteristic of a "Madison-like" climate.

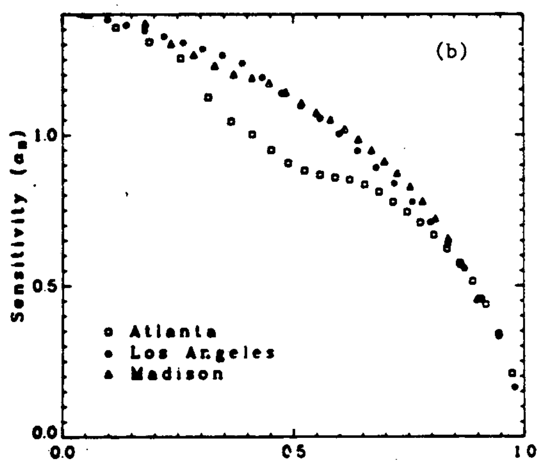

Fig. 2(b). *The sensitivity parameter α for global horizontal radiation.*

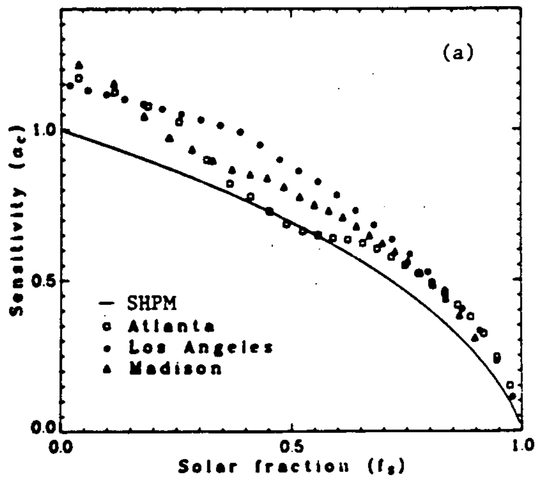

Fig. 2(a). *The sensitivity parameter α for errors in solar radiation incident on the collector surface.*

$$c_s = C_s/E_s\ , \tag{8}$$

for comparison to, say, the cost per unit of energy from fossil fuel. For a fixed collector area and a specified load, E_L, it is straightforward to show that

$$\delta c_s = -\alpha \cdot \delta I. \tag{9}$$

For a solar system that was designed to supply 50% of the load, a representative value from Fig. 2 would be $\alpha = 1.00$ for horizontal surface solar data. Suppose that the data were overestimated by 10% ($\delta I = 0.10$). Then the actual cost per unit of usable solar energy would be 10% greater than predicted. Grossly overestimated solar data may cause buildings to be equipped with solar systems when, if economics were the primary criterion, they should not be.

Now consider a situation in which the solar data are underestimated. Suppose, further, that the design was for a solar fraction of 75%, for which a representative value would be $\alpha = 0.70$. If the data are too low by 20% ($\delta I = -0.20$), then the actual cost per unit of usable energy will be 14% less than predicted. Grossly underestimated data may deter the construction of solar systems because of artifically high cost predictions.

5. ECONOMICS OF OPTIMIZED SYSTEMS

If the solar system is economically competitive with the conventional alternative, then there will generally be some collector area which will optimize the system (yield mimimum overall costs). If the solar data used in the optimization are in error, then the collector area will be non-optimum when the system is actually operated and there will be a corresponding cost penalty. To investigate this penalty a simplified cost analysis is adapted. In this analysis the total cost (solar plus backup), C, is given by

$$C = (1-f_s) \cdot C_c + C_f + c_A \cdot A \tag{10}$$

where C_c is the fuel cost of supplying the entire load by conventional means, C_f any fixed cost of the solar system, and c_A the cost per unit of collector area. The solar system will be judged economical if there is some collector area for which

$$C < C_c. \tag{11}$$

That is, the combined solar-backup system is less expensive than supplying the same amount of energy by a conventional system alone. [The costs may refer to life-cycle or to present yearly costs, depending on the preference of the decision maker.] The optimization consists of determining the collector area that minimizes C,

$$\partial C/\partial A = 0$$

It can then be shown through a series expansion that:

$$\delta C = (C_c/C_a) \cdot \beta \cdot (\delta I)^2, \tag{12}$$

where C_a is the cost had the actual (correct)

Secondly, most available solar data are the global radiation on a horizontal surface. Solar collectors, on the other hand, are usually tilted towards the equator or maintained normal to the sun. [In models such as FCHART some method is used to transform the radiation from the horizontal to the collector surface.] Rather than limiting the analysis to either global horizontal or collector surface radiation the sensitivity parameter α has been calculated for both cases.

Turning again to Fig. 2, the results are similiar for the three climate types and show the same general behavior as for the SHPM: a sensitivity to solar data errors that decreases with increasing solar fraction. For low solar fractions α can be greater than 1.0, and the performance of the system is quite sensitive to errors in the solar data. For high solar fractions α tends towards zero, and such systems are relatively insensitive to errors.

There are several other features in Fig. 2 that merit discussion. The first is that the values for the solar heating case generally exceed those of the SHPM. This is the true even for Los Angeles where (see Fig. 1) the dependence of the solar fraction on collector area is almost indistinguishable from that of the SHPM. The explanation has to do with the assumption used in deriving the SHPM that a fractional change in incident solar radiation is equivalent to the same fractional change in collector area. In reality there is a threshold solar radiation value, below which a collector will have no usable output. Increasing the solar radiation above the threshold can result in usable output energy, whereas increasing the collector area (while the solar radiation remains below the threshold value) will not produce usable output.

The second feature is that α_H [Fig 2(b)] is systematically larger than α_C [Fig. 2(a)], indicating that the system is more sensitive to errors in global horizontal data than to errors in data for the collector surface. For the climates considered here, and for the months with significant heating loads, the horizontal to collector surface transformation used in FCHART is such that errors in the horizontal radiation propagate into larger errors in the collector surface radiation.

The third feature is that the curves, specially for Madison and Atlanta, display some structure. In FCHART the annual solar fraction for any given collector area is a weighted (by heating load) sum of the twelve monthly values. It is the month-to-month variations that, added together, lead to the observed structure.

4. COST OF THE SOLAR SYSTEM

Let C_s be the installed cost of the solar system. Depending on the type of economic analysis used by the potential purchaser of the system, C_s might be the total cost of the system or the annual payment on a loan. For present purposes this distinction is not of importance.

Consider a purchaser interested in knowing the cost per unit of usable solar energy, data been used in the optimization, and δC is the fractional change in total cost due to the use of erroneous data. Note that the first factor in Eq. (12) is the ratio of the cost of supplying the entire load by conventional means to the cost of the (correctly) optimized solar system. From Eq. (11), this ratio will be greater than but usually on the order of 1.0. β is a dimensionless parameter that describes the sensitivity of the cost to the (square of the) error in the solar data. For the SHPM, and as for α, β is a function of only the solar fraction.

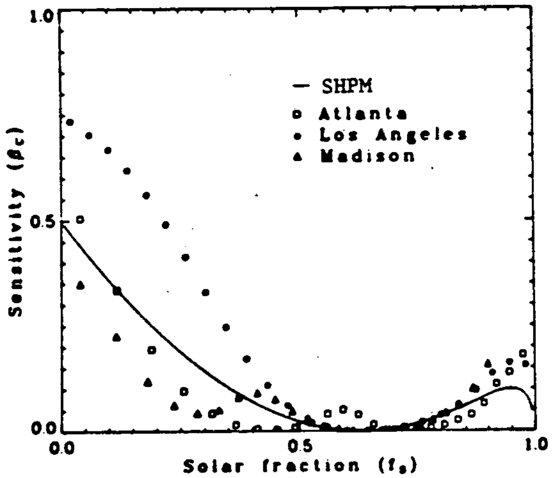

Fig. 3. *The sensitivity parameter β for errors in solar radiation incident on the collector surface.*

The parameter β is plotted against the solar fraction in Fig. 3 for the SHPM and the solar heating system. As compared to α, β shows a greater deviation from the SHPM and a greater dependence on whether the solar data are for the global horizontal radiation (not shown) or the collector surface radiation. However, the general trends are similar for all the cases. Note, first, that β is always positive. Thus the fractional change in cost is always positive (there is always a cost penalty) regardless of whether the solar radiation is too high or too low. However, the penalty will often be quite small. For all the cases studied here β is less than 0.20 for solar fractions from about 0.4 up to 0.8. For this value, and for an error in the solar radiation of 20%, the fractional increase in cost would be only about 0.8%. β is essentially zero for solar fractions on the order of 0.63, meaning that (at $f_s = 0.63$) there is essentially no cost penalty for having optimized with erroneous data.

It may be considered surprising that the cost penalty of using inaccurate data would be only about 1%. The explanation is that near the optimum point the increased cost of having "too much" collector area is nearly offset by the decreased cost of the backup energy. Similarly, the increased cost of the backup energy when the collector area is undersized is roughly balanced by the decreased cost of the collectors.

6. CONCLUSIONS AND REMARKS

A framework has been presented for examining the sensitivity of the performance and cost of solar system designs to errors in the solar data. For low solar fractions, and especially for horizontal surface data, the estimated performance and the estimated cost per unit of usable solar energy can be quite sensitive to the errors. For example, for a solar fraction of 0.25, solar data that are underestimated by 20% could result in nearly a 30% overestimate in the cost per unit of usable solar energy. Systems with large solar fractions are less sensitive; for a system with a solar fraction of 0.75 the same error in the solar data would result in, roughly, a 14% overestimate of costs. Any given decision maker for one or a few building units will be influenced by a host of factors in addition to the estimated cost. However, economic considerations will affect decisions on the margin. Thus underestimated solar data will influence the average behavior of the community so as to deter the purchase of solar energy systems. Similarly, overestimated data will lead to an underestimate of the cost per unit of usable energy and lead to the construction of solar systems that are not economically justified.

Also developed was an expression for the total cost (solar plus backup) penalty for having optimized a solar system with inaccurate solar data. The analysis shows that the penalty is less than 1% for modest solar fractions. For the individual, a cost penalty of this size is essentially negligible. For a larger community, however, the cumulative cost penalty from many improperly optimized systems can be substantial. This cumulative cost can be estimated given a scenario of future construction of solar energy systems (Berdahl, et al., 1978). This estimated cost can be compared to that of establishing, improving, or maintaining a network of accurate solar data measurement stations.

7. REFERENCES

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