A COMPARATIVE STUDY OF METHODS FOR ESTIMATING INTERCEPT FACTOR OF PARABOLIC TROUGH COLLECTORS

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ABSTRACT

One of the parameters used for the evaluation of a parabolic trough collector performance is optical efficiency. This depends on the properties of the various materials employed in the construction of the collector, the collector dimensions, the angle of incidence and the intercept factor (γ). The intercept factor depends on the size of the receiver, the surface angle errors of the parabolic mirror, and on solar beam spread. A ray-trace computer code called EDEP (Energy DEPosition computer code) is used by Guven and Bannerot (1985) to calculate the intercept factor. The intercept factor can also be calculated by a closed-form expression developed by Guven and Bannerot (1985). This expression considers both random and non-random errors. These errors are encountered in the construction and/or in the operation of the collector. An artificial neural network was trained to learn the γ-values based on the input data of collector rim angle, random and non-random errors, and the EDEP results. The output is compared with the EDEP results which are considered to be the most accurate, the results of a simple program developed by Guven (1987) using the trapezoidal integration method, and a multiple linear regression analysis. From all the above it is shown that the results obtained by the artificial neural network system approximates the results of the ray-trace model, extremely well with an R^2-value equal to 0.999.

INTRODUCTION

In order to obtain temperatures higher than about 100°C, with low density solar radiation, concentrating collectors are used. A particular type, the parabolic trough collector (PTC), is currently receiving considerable attention. Typical applications of PTC's vary from hot water production (typically 60°C) to steam generation used for power and industrial process heat applications (up to 350°C).

Parabolic trough collectors are structurally simpler than other types of collectors (i.e. flat-plate collectors) although some form of tracking must be employed and the parabolic surface must be accurate, to ensure high efficiency.

The power of neural networks in modelling complex mappings, and in implementing system identification has been demonstrated in various occasions by Kohonen (1984), Ito (1992) and many others. Their work encouraged many researchers to explore the possibility of using neural network models in real word applications such as control systems, data classification, and modelling of complex process transformations.

The aim of this study is to investigate the possibility of using neural networks for predicting the intercept factor of parabolic trough collectors. The prediction will subsequently be compared with the EDEP (Energy DEPosition computer code) results which are considered to be the most accurate, the results of a simple program developed by Guven (1987) using the trapezoidal integration method, and a multiple linear regression analysis.

INTERCEPT FACTOR

The performance of a PTC depends on many parameters. One of them is the optical efficiency which is defined as the ratio of the energy absorbed by the receiver to the energy incident on the concentrator's aperture. The optical efficiency depends on the optical properties of the various materials involved, the geometry of the collector, and the various errors encountered in the construction and/or in the operation of the collector. These errors affect the intercept factor which is defined as the ratio of the energy intercepted by the receiver to the energy reflected by the focusing device, i.e. parabola (Sodha *et al.*, 1984). Its value depends on the size of the receiver, the surface angle errors of the parabolic mirror, and solar beam spread.

The errors associated with the parabolic surface are of two types, random and non-random (Guven and Bannerot, 1985). Random errors are defined as those errors which are truly random in nature and, therefore, can be represented by normal probability distributions. Random errors are identified as apparent changes in the sun's width, scattering effects caused by random slope errors (i.e. distortion of the parabola due to wind loading) and scattering effects associated with the reflective surface. Non-random errors arise in manufacture/assembly and/or in the operation of the collector. These can be identified as reflector profile imperfections, misalignment errors and receiver location errors. Random errors are modelled statistically, by determining the standard deviation of the total reflected energy distribution, at normal incidence (Guven and Bannerot, 1986) as specified in equation 1.

$$\sigma = \sqrt{\sigma_{sun}^2 + 4\,\sigma_{slope}^2 + \sigma_{mirror}^2} \tag{1}$$

where: σ_{sun} Standard deviation of the energy distribution of the sun's rays at normal incidence.
σ_{slope} Standard deviation of the distribution of local slope errors at normal incidence.
σ_{mirror} Standard deviation of the variation in diffusivity of the reflective material at normal incidence.

Non-random errors are determined from a knowledge of the misalignment angle error β (i.e. the angle between the reflected ray from the centre of sun and the normal to the reflector's aperture plane) and the displacement of the receiver from the focus of the parabola (dr). The reflector profile errors and the receiver mislocation along the y-axis essentially have the same effect, thus a single parameter is used to account for both. According to Guven and Bannerot (1986) random and non-random errors can be combined with the collector geometric parameters, concentration ratio (C) and receiver diameter (D), to yield error parameters universal to all collector geometries. These are called "universal error parameters" and an asterisk is used to distinguish them from the already defined parameters. Using the universal error parameters the formulation of the intercept factor γ (gamma) is derived as follows (Guven and Bannerot, 1985):

$$\gamma = \frac{1+\cos\phi_r}{2\sin\phi_r}\int_0^{\phi_r}\left\{ Erf\left(\frac{(\sin\phi_r)(1+\cos\phi)(1-2d^*\sin\phi) - \pi\beta^*(1+\cos\phi_r)}{\sqrt{2}\pi\sigma^*(1+\cos\phi_r)}\right) - Erf\left(-\frac{(\sin\phi_r)(1+\cos\phi)(1+2d^*\sin\phi) + \pi\beta^*(1+\cos\phi_r)}{\sqrt{2}\pi\sigma^*(1+\cos\phi_r)}\right)\right\}\frac{d\phi}{(1+\cos\phi)} \tag{2}$$

where:
φ_r Rim angle (degrees)
σ^* Universal random error parameter ($\sigma^*=\sigma C$)
β^* Universal non-random error parameter due to angular errors ($\beta^*=\beta C$)

d^* Universal non-random error parameter due to receiver mislocation and reflector profile errors (d^*=dr/D)

INTERCEPT FACTOR ESTIMATION USING AN ARTIFICIAL NEURAL NETWORK

Data estimated with the EDEP program, which is considered as being the most accurate, have been used to train an artificial neural network. The input data is a set of values of collector rim angle, universal random error parameter (σ^*), universal non-random error parameter due to angular errors (β^*), and universal non-random error parameter due to receiver mislocation and reflector profile errors (d^*). A Ward type network architecture (Neuroshell 2) of three neurons in each hidden layer has been used. Other architectures have been tried with somewhat similar results, but the one presented has the best overall performance both in the training and the evaluation phases. This architecture allows multiple hidden layers with different activation functions. Four input neurons have been used, corresponding to the values of the input parameters listed above as a four-element input vector of the training data set. The output is a single-element corresponding to the values of γ estimated by the EDEP program. The gain was set to 0.1 and the momentum to 0.5. The weights were initialised to a value of 0.3. The training data set was composed of 50 patterns while the unknown data set of 9. The learning algorithm used was the standard backpropagation. The results of this study are summarised in Fig. 1 where the difference in predicted values of ã and the values given by EDEP are plotted against ã for each method. It is noted that the input data for the case of the ANN model were learned with excellent accuracy.

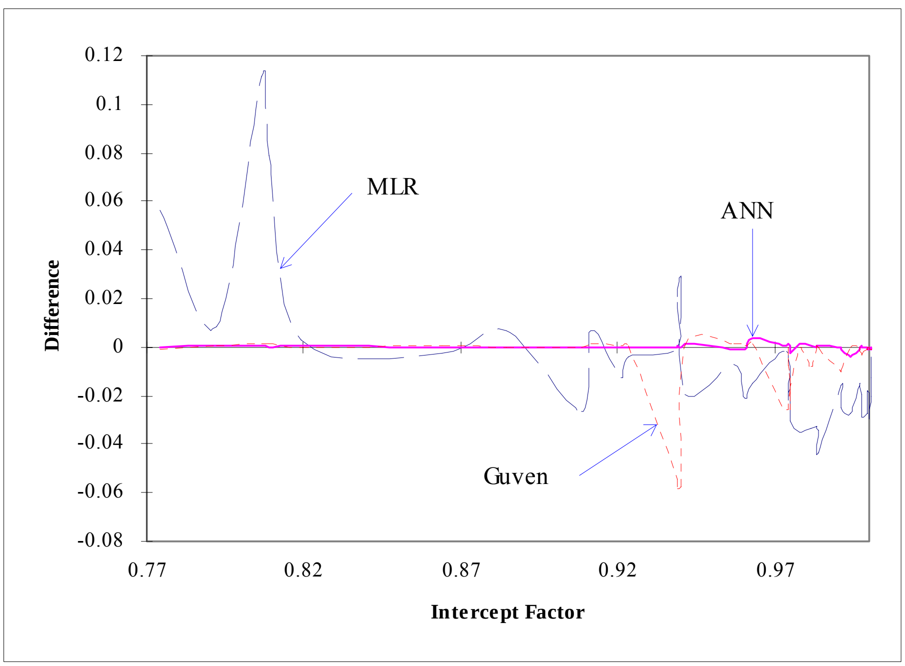

Fig. 1. Differences in predicted values of intercept factor and the values given by EDEP for each method.

CONCLUSIONS

From the data presented in Fig. 1 can be concluded that the ANN method estimates the collector intercept factor accurately. The correlation coefficients and R^2-values of the neural network system, of the program developed by Guven (1987) using the trapezoidal integration method to solve Equation (2), and a multiple linear regression analysis (MLR) as compared to the ray-trace program EDEP (learning set) are shown in Table 1.

Table 1. Comparison of intercept factor obtained from different programs

Parameter	ANN	Guven	MLR
Correlation coefficient	1.000	0.976	0.874
R^2-value	0.999	0.953	0.763

It can be seen from Table 1 that the prediction of the artificial neural network program presented here calculates γ closer to the EDEP results than any of the other methods considered. The maximum percentage difference between EDEP and the new program is 0.4% whereas the corresponding difference between EDEP and the program developed by Guven is 6.2% (Guven, 1987). Therefore it can be concluded that the ANN system can be used confidently for evaluating the intercept factor of a parabolic trough collector.

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