Artificial Neural Network for Predicting the Local Concentration Ratio of Parabolic Trough Collectors

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ABSTRACT:- The concentrated radiant flux on receiver surfaces of parabolic trough collectors is not uniform but exhibits a "bell" type shape as presented in this paper. This flux is given in terms of the local concentration ratio (LCR) being in effect the ratio of the incoming to the concentrated value of solar radiation at the periphery of the receiver. Knowledge of the LCR is required not only at normal conditions but also at various incident angles. This is useful to a designer who wants to calculate the intercept factor and the optical efficiency of the concentrator at those angles. In the work presented here actual values of LCRs, at ten degree intervals around the receiver, for two different incident angles (15° and 60°) are used to train an artificial neural network. Subsequently the network is used to predict the LCR values at other incident angles. The matching of the data for the 15° and 60° is very good with an R^2-value equal to 0.9997. For the unknown data at incident angles of 0°, 30° and 45° the R^2-values are 0.9966, 0,9867 and 0.9765 respectively which indicates that the estimation is performed with adequate accuracy. By using the predicted LCR values, the intercept factor is estimated with a maximum deviation of 3.2% from the value estimated with the actual LCR values which is very adequate.

1. INTRODUCTION

Parabolic trough collectors are employed for a variety of applications including industrial steam production and hot water production. Parabolic trough collectors are preferred for high temperature applications because these can be obtained without any serious degradation of the collector efficiency.
One measure of performance of a PTC 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 in the construction of the collector, the geometry of the collector, and the various imperfections arising from the construction 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 (parabola). Its value depends on the size of the receiver, the surface angle errors of the parabolic mirror, and solar beam spread.
The power of neural networks in modelling complex mappings has been demonstrated by Kohonen (1984), Ito (1992) and many others. Their work encouraged many researchers to explore possibilities of using neural network models in real world applications such as in control systems and in modelling complex process transformations.
The aim of this study is to investigate the possibility of using neural networks for predicting the local concentration ratio (LCR) of parabolic trough collectors which can be used subsequently for estimating the collector intercept factor and optical efficiency. The LCR value depends on many parameters as will be shown later but the main ones are the incidence angle and the angular position on the receiver. For this mapping a set of LCR values at equal angular increments will be used for two particular incident angles. The trained network will then be used to predict the LCR at the same angular positions on the receiver but at other incident angles.

2. LOCAL CONCENTRATION RATIO

The receiver is the heart of the parabolic trough collector system and consists of a copper or steel pipe surrounded by a glass envelope. The solar radiation falling on the collector aperture is reflected and concentrated onto the receiver. As shown by Jetter (1987) the radiation profile on the receiver is not uniform. It is usually expressed as the local concentration ratio (LCR) i.e. the ratio of the concentrated to the incoming radiation. The LCR depends on the angle β, shown in Fig. 1, the incidence angle Θ, the total standard deviation of the errors, and the collector geometric parameters. Jetter (1987) developed an analytical method for the calculation of LCR values which involves knowledge of all the above parameters and a complex mathematical analysis.

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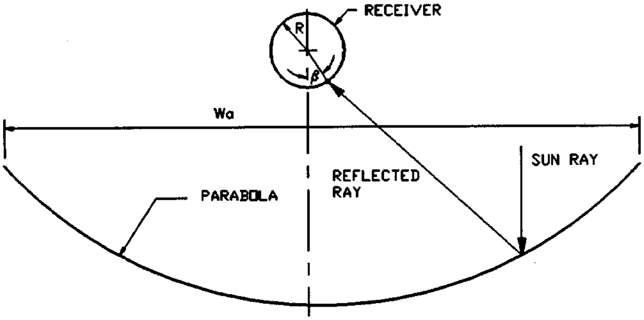

Fig. 1. Parabolic trough collector

Typical LCR values for a PTC collector are shown in Fig. 2 for various incident angles as indicated. As the distribution is symmetrical about a vertical axis, only half of the graph is shown. Similar results, with respect to the shape of the distribution were obtained by Thomas et al. (1986) by using a CdS photoresistor mounted on the periphery of a cylindrical ebonite tube, at full moon. Similar results were also obtained by the author by using an eye response photodiode mounted on an attachment fitted on a bevel protractor and thus being able to move accurately around the periphery of the receiver. By measuring the current produced by such a device first directly facing the sun, at normal incidence angle and then around the receiver at various steps of the angle β, the LCR values can be obtained by the ratio of the electric current recorded at the particular angle to the normal one.
It can be shown that by integrating the flux density over the entire absorber and dividing by the incidence irradiance yields the intercept factor as (Jetter, 1987):

$$\gamma = \frac{\int LCR\ (R\ d\beta)}{Wa} \qquad (1)$$

where: R Receiver radius
β Angle shown in Fig. 1
Wa Collector aperture (see Fig. 1)

The optical efficiency is given by:

$$\eta_o = \rho\ \tau\ \alpha\ \gamma \qquad (2)$$

where: ρ Mirror reflectance
τ Receiver cover transmittance
α Receiver absorptance

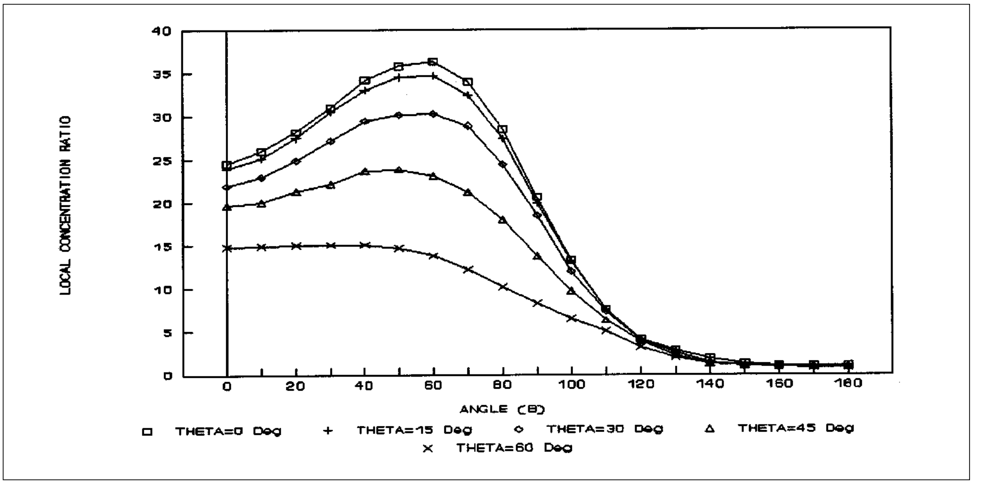

Fig. 2. Variation of LCR-values with angle β for different incidence angles

It can be understood from the relations above that knowledge of the LCR values at different β-angles can be used to determine both γ and n_0. Such a calculation is usually required not only at normal conditions but also at various incident angles which can be used to estimate the incidence angle modifier, a correlation factor accounting for off-normal incidence effects on optical efficiency. It should be noted that the values of ρ, τ and α in Eq. (2) are incidence angle dependent. By using appropriate values for normal incidence together with the intercept factor estimated at that angle, the maximum optical efficiency of the collector can be determined. At other incidence angles the values of ρ, τ and α are changed according to the material properties and should be taken into consideration.

3. ARTIFICIAL NEURAL NETWORK

Data for the two cases (shown in Fig. 2) for incident angles 15° and 60° are used to train an artificial neural network. Values from actual experiments are used for this training and therefore the collector geometric parameters and the total standard deviation of errors are automatically considered. The actual data is a set of values of angle β, incident angle Θ, which is constant for the particular set, and the LCR values corresponding to each angle β. It should be noted that it is very difficult, due to size limitations to test E-W oriented collectors at normal incidence. However, data at this angle are required for the estimation of the maximum optical efficiency. The network architecture used is the Ward type 2 consisting of five neurons in each hidden layer. The Ward type architectures allow multiple hidden slabs with different activation functions. Two input neurons have been used, corresponding to the values of β and Θ of the two-element input vectors of the training data set. The output is a single element vector corresponding to the values of LCR. The gain was set to 0.1 and the momentum to 0.5. The input layer activation transfer function was chosen to be linear, while the transfer function used in the other layers is as shown in Fig. 3 where the structure of the Ward type 2 network is presented. The weights were initialised to a value of 0.3. The training data set has 35 patterns while the test data set has 3. The learning algorithm used was the standard backpropagation. The input data were learned, as shown in Fig. 4, with excellent accuracy with R^2-value equal to 0.9997. In fact, the matching between predicted and measured values is so close that the two lines are almost indistinguishable. It is expected by the network to learn not only the variation of LCR with β but also to incorporate the incidence angle Θ so as to be able to predict LCRs at the same angles β but at different incidence angles. That is actually why two sets of data, at different incident angles, are required for learning.
After the network was trained it was used to predict the LCR values at incidence angles of 0°, 30° and 45° which are completely unknown data for the network. The predicted values

compared well with the actual data as shown in Figs. 5, 6 and 7. Table 1 gives a summary of R^2-values and the correlation coefficients for this prediction together with the percentage error in γ estimation resulting from the LCR values predicted. It is evident from these results that the proposed method can be used effectively for LCR prediction and for the calculation of the intercept factor of parabolic trough collectors.

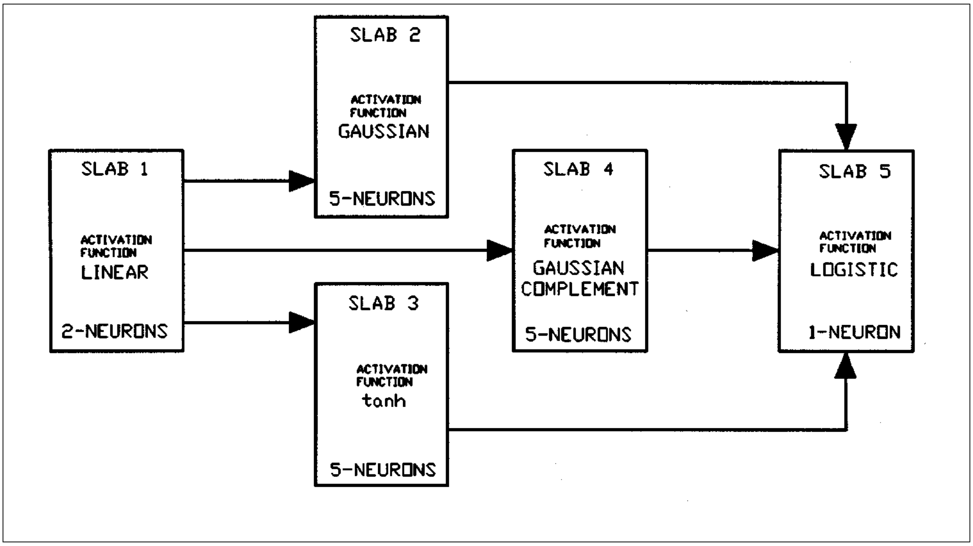

Fig. 3. Structure of the Ward type 2 network

Incidence Angle (Deg)	R^2–value	Correlation Coefficient	Percentage error in γ estimation
0°	0.9966	1.000	3.2
30°	0.9867	0.995	2.6
45°	0.9765	0.990	2.0

Table 1. Statistical analysis of program predictions and resulting percentage error in estimation of intercept factor

CONCLUSIONS

A neural network is trained with two sets of data of LCRs for 15° and 60°. It has been shown that the network achieved excellent mapping and it has been used subsequently for predicting the LCR values at other incidence angles i.e. 0°, 30° and 45°. The prediction at these angles is done with good accuracy and correlation coefficients equal or very close to unity are obtained, which is an indication that the prediction is very near to the actual data. By using the predicted LCR values, the intercept factor is estimated with a maximum deviation of 3.2% from the value estimated with the actual LCR values which is very adequate. Therefore the method can successfully be used for estimating the LCR values provided that at least two sets of such data are available for two distinct incident angles. The method can easily be applied by workers in the field of concentrating collectors and will

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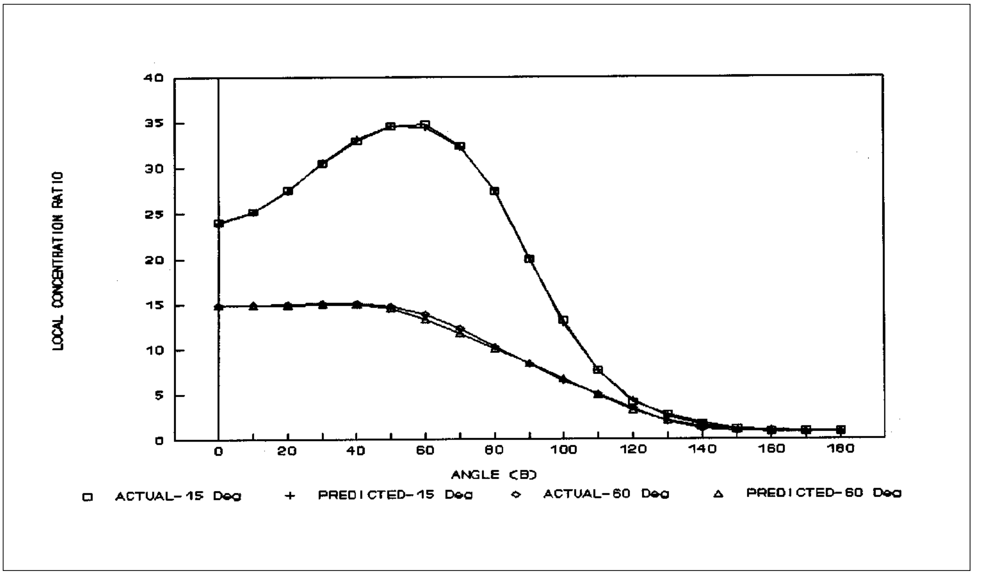

Fig. 4 Comparison of predicted and actual LCR values for incidence angles of 15° and 60° (learning mode)

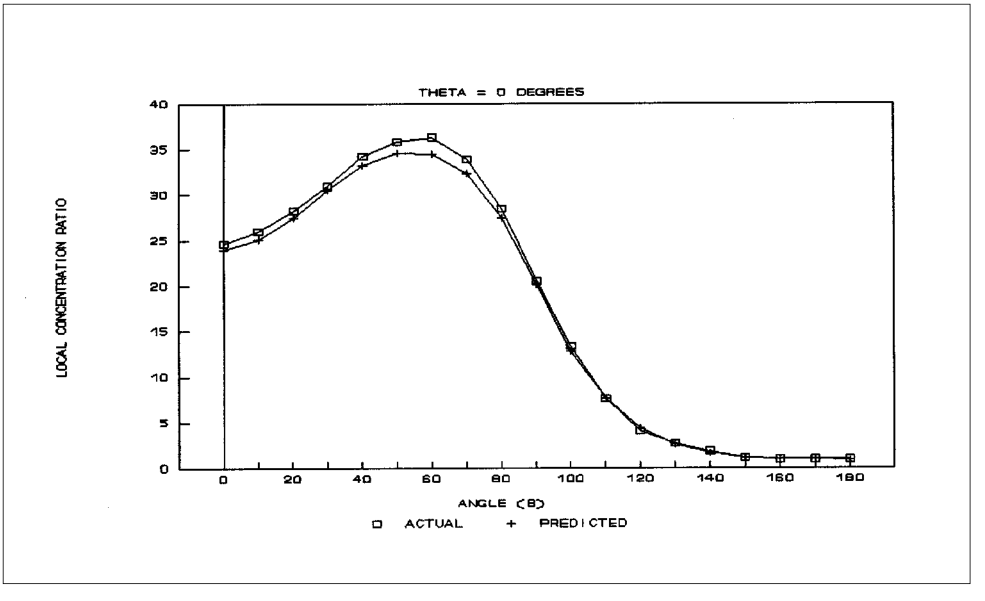

Fig. 5 Comparison of predicted and actual LCR values (Theta = 0°) (completely unknown data)

facilitate greatly their estimations. It is a simple method which does not require knowledge of complex parameters, like the standard deviation of the errors, or complex methematics. The use of neural networks may be considered for application to other complex fields of solar energy such as in steam generation systems and water heating systems.

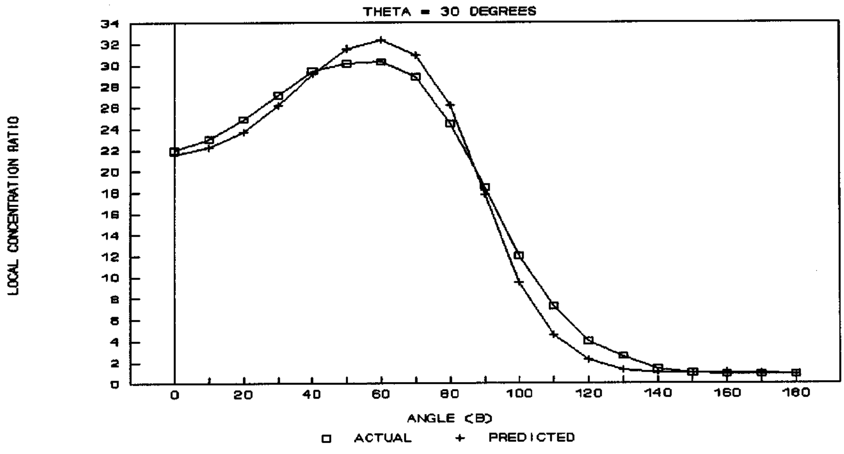

Fig. 6 Comparison of predicted and actual LCR values (Theta = 30°) (completely unknown data)

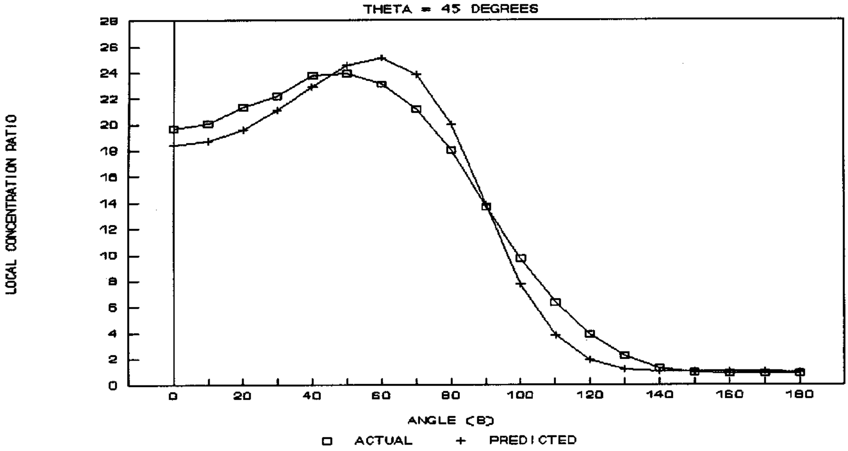

Fig. 7 Comparison of predicted and actual LCR values (Theta = 45°) (completely unknown data)

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