Middle-East Journal of Scientific Research 24 (2): 239-243, 2016
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2016.24.02.22895

Predictive Validation of Inversion Temperatures in a Non-Convective pool Subjected to Multiple Absorbing Layers, Using Curvilinear Regression Models

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Abstract: In the present investigation, predictive validation of inversion temperatures in a non-convective pool subjected to multiple absorbing layers using curvilinear regression model is presented. Temperature data were obtained using four experimental model pools D_1, D_2, D_3 and D_0 with one, two, three and zero absorbing layers respectively (transparent glass material of thickness measuring 0.5 cm), inserted with high accuracy mercury in-glass thermometers. The model pools were drums of height measuring 83.0 cm, perforated at graduated distances and lagged with insulating materials (styropor) of thickness measuring 2.5 cm. The multiple absorbing layers were placed on top of the drums at interval distances of 10.0 cm between them to trap radiant energy and increase the heating effect. Temperature monitoring was carried out between 6 am and 6 pm for two distinct seasons (dry and wet seasons) on hourly basis. The temperature data obtained were analyzed using statistical package (SPSS) to generate curvilinear regression model equations. Results obtained from this study showed that the predictive equations generated for determination of inversion temperature points were significant at certain periods of the day for pools D_2 and D_3, as the test for model fit was done at p = 0.05 significant level. The result shows that, the validity of the predictive model depends on the number of the absorbing layers.

Key words: Predictive equations · Inversion · Multiple absorbing layers · Temperature

INTRODUCTION

Solar energy research in passive systems span from thermosyphone, solar pond technology, solar water heater (water still) and a host of other passive systems. In all these, the application of glazing collectors or absorbing layers in solving energy problems have produced enhanced energy output in these systems and this has a direct correlation with the volume of solar radiation received by the collector surfaces [1-5].

Study in the occurrence of successive temperatures inversion in a non-convective pool subjected to multiple absorbing layers showed that the passive systems use specifically buoyancy induced force in transferring energy from one point in the collector to another. This eliminates the need for force pumps or moving part control that create the required force for energy transfer [6, 7-8]. The buoyancy induced force in the passive systems is generated by the temperature gradient [9]. Temperature gradient is the rate of change of temperature with displacement in a given reference point. At sea level, a temperature gradient is the change of temperature with depth; a positive gradient is a temperature increase with an increase in depth and a negative gradient is a temperature decrease with an increase in depth [2, 5].

Convection remains the dominant mode of energy transport when the temperature gradient is steep enough such that a given parcel of gas within the sky will continue to rise. It rises slightly through an adiabatic process [10-12]. The mathematical equation for temperature gradient is given thus;

$$\frac{dT}{dx} = \left(\frac{dT_2}{dx_2} - \frac{dT_1}{dx_1} \right) \quad (1)$$

where dT_1 and dT_2 are changes in temperatures, dx_1 and dx_2 are changes in heights. But dT over dx, is the temperature gradient.

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The storage level of any non-convective pool is a function of the quantum of the solar energy received by the collector surface which invariably affects the distribution level of the energy in it [13]. However, the process of transferring energy through any passive system follows a linear pattern as noted by research [1, 11]. However, one important thing to note about a non-convective pool is its performance based on liquid stratification. This defines the existence of temperature gradient within the different layers of the liquid. Stratification of thermal energy is represented by the transient temperature profiles under different thermal, fluid dynamics and geometric conditions [10, 12]. Note that, under certain conditions there is a predefined temperature gradient that will cause the convectional liquid flow direction to reverse resulting to partial discharge of thermal storage i. e. $\frac{dT}{dx} = 0$. This occurs during a standby period due to non-solar intake from the heat exchange loop. It could also be that the cooler fluid is circulated through the warm liquid layer thereby removing heat from the heat exchange loop [8].

Hence, the removal of heat or non-solar intake results to a sudden fall in temperature which is referred to as temperature inversion. More so, the excessive release of heat could cause an abnormal increase in temperature, called temperature inversion [9]. Fig. 1 gives a dimensional model of inversion temperature in non-convective pool with multiple absorbing layers.

Incident and Reflected Radiant energy

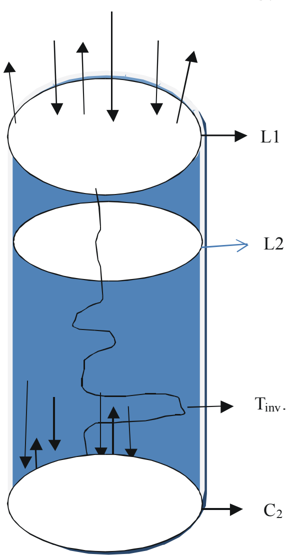

Fig. 1: Dimensional model of inversion temperature in non-convective pool with multiple absorbing layers

where L_1 and L_2 are absorbing layers, C_1 is the bottom collector, T_{inv} is the inversion temperature.

To validate the status of the data, curvilinear regression model equations that describe the relationship between dependent variable (temperature) and the independent variables (height, number of absorbing layer and time of the day) were used to estimate the inversion temperature points using an equation of the form;

$$y = a + b_1 x + b_2 x^2 \qquad (2)$$

were generated, where y represents the temperature variable, x and x^2 are combinations of other factors such as; height, of time of the day and number of absorbing layers [1].

MATERIALS AND METHODS

The research was carried out in two seasons (Dry and Wet) and used four experimental non-convective pools (steel drums) of diameter measuring 57.0 cm and height of 83.0 cm. Eleven thermometers were inserted at designated heights measured from the base of the pools. The thermometers occupied the drum height measuring between 7.0 cm to 63.0 cm. The process of lagging was carried out by using insulators (styropo) of thickness measuring 2.5 cm, followed by the introduction of a volume of water measuring up to 60.0 cm of the drum height. Finally, multiple absorbing layers (glass collector covers) were fitted into the drums. Drum 1 carried 1-glass, drum 2, carried 2-glasses, drum 3 carried 3-glasses and drum 4 had no glass. The last set of glasses covered the surfaces of the drums; the second and the third set were separated by a distance of 10 cm from each other fitted into the drums. The experimental setup was carried out in an open field devoid of shade and placed on top of 6 inches thick blocks above the ground. This was to avoid interference and create maximum solar radiation reception from all angles. The inner surfaces of the pools were painted with black red oxide paint to conserve heat as described by [3]. The values of temperature variation with height for four non-convective pools were monitored between 6 am to 6 pm daily for the period of time stated. The data were tabulated and statistical analysis made using Analysis of variance (ANOVA), curvilinear regression equations for one hour in a particular time of the day were generated and the models tested at p = 0.05 significant levels. The results are shown on Tables 1-4.

RESULTS AND DISCUSSION

The result on Table 1 shows some similarities in the nature of data and the trend of temperature distribution bearing in mind the linearity and the non-linearity in some cases. The observed data had the maximum values of temperature ranging from 48.5°C for pool 1, followed by pool 2, 45.0°C, pool 3, 40.4°C and finally 38.8°C for pool 4. The inversion temperatures occurred across the pools with pool (D1) having it at 49.0 cm, pool 2 (D_2) at 35.0 cm and pool 3 (D_3) at 21.0 cm. The inversion temperature values ranges between 01°C to 15.0°C across the four non-convective pools as shown on Table 1:

From Table 2, the total variations in temperature values are accounted for by the number of absorbing layers and the heights of the pools. The p-value of 0.013 associated with the computed data is less than the chosen level of significance of 0.05. This shows that the model is significant.

Figure 2 gives the P-P Plot that was used to predict the validity of the model. Though the distribution of the data on the plot is not completely linear, the variation in the scatter points is relatively negligible and thus indicate that the model is significant.

From Table 3, the prediction model equation is as follows;

$$T = 37.132 - 0.734x + 0.13x^2$$

$$\frac{dT}{dx} = -0.734 + 0.26$$

$$x = \frac{0.734}{0.026}$$

The point of inversion is obtained when; $\frac{dT}{dx} = 0.$

$x = 28.23$ cm

The prediction equation for model D_2 at 12noon is;

$T = 37.132 - 0.734x + 0.13x^2$

From Table 4, about 71.2 % of the total variations in temperature values are accounted for the number of absorbing layers and the heights of the pools. The P- value 0.007 associated with the computed data is less than the chosen levels of significance of 0.05. It shows that the model is significant.

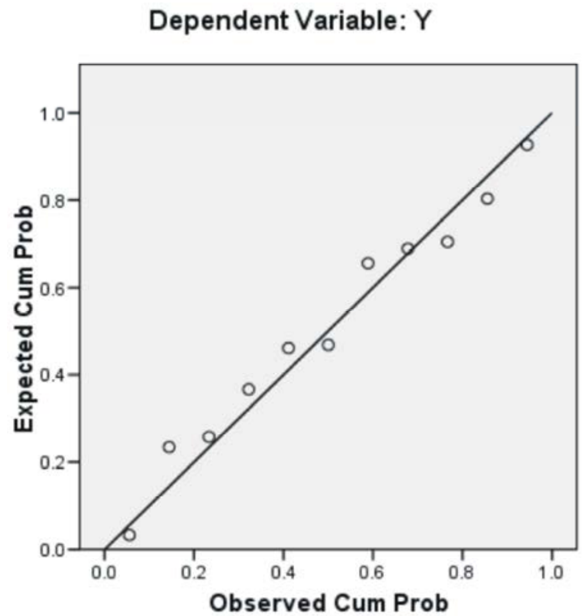

Fig. 2: Normal P-P Plot of Regression Standardized Residual for Model D_2 at 12 noon

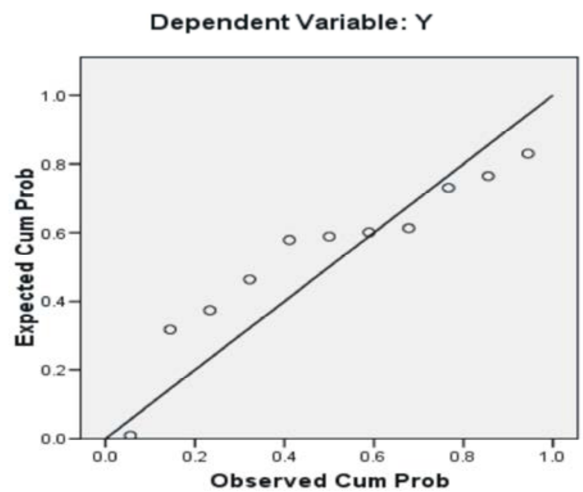

Fig. 3: Normal P-P Plot of Regression Standardized Residual for Model D_3 at 12 noon

Figure 3 gives the normal P-P Plot of Regression Standardized Residual for Model D_3 at 12 noon. The P-P Plot is used to predict the validity of the model as shown on Figure 3. Though the model is significant, but from the distribution of data based on the observed cumulative probability departure from the expected, it shows clearly that models are based on estimation theory and not practical.

From Table 5, the prediction model equation is as follows;

Table 1: Temperature Distribution with Height for four Non-Convective Pools at 12 pm, Ta = 35.2°C

Height (cm)	D_0 Temp(°C)	D_1 Temp(°C)	D_2 Temp(°C)	D_3 Temp(°C)
7.0	27.0	30.1	29.9	29.4
14.0	27.5	30.1	31.0	30.0
21.0	27.0	31.2	29.5	21.0
28.0	26.8	31.1	32.6	31.0
35.0	29.0	29.0	20.9	31.2
42.0	28.3	30.9	32.0	32.0
45.5	28.0	32.0	31.2	33.0
49.0	29.9	22.0	33.0	33.5
52.5	31.0	34.0	33.1	33.9
56.0	31.1	36.9	36.8	36.0
63.0	33.8	48.5	45.0	40.4

Table 2: Summary of Statistical Analysis for the Predictors (x,x^2) and Dependent Variable (Y) for Model D_2 at 12noon

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.815(a)	0.664	0.581	3.78878

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	227.418	2	113.709	7.921	0.013(a)
	Residual	114.839	8	14.355		
	Total	342.256	10			

a Predictors: (Constant), (x, x_2) = height

b Dependent Variable: y = temperature

Table 3: Summary of Parameters Coefficient (x,x^2) for the Model D_2 at 12 Noon

		Unstandardized Coefficients		Standardized Coefficients		
		---		------------------------------	T	Sig.
Model		B	Std. Error	Beta	B	Std. Error
1	(Constant)	37.132	4S.837		7.676	0.000
		-0.734	0.321	-2.240	-2.288	0.051
		0.13	0.005	2.858	2.918	0.019

a Dependent variable: T

Table 4: Summary of Statistical Analysis for the Predictors (x,x^2) and Dependent Variable (Y) for Model D_3 at 12 Noon

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.844(a)	0.712	0.640	2.85820

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	161.433	2	80.716	9.880	0.007(a)
	Residual	65.355	8	8.169		
	Total	226.787	10			

a Predictors: (Constant), (x,x^2) =height

b Dependent Variable: y = temperature

Table 5: Summary of Parameters Coefficient (x,x^2) for the Model D_3 at 12 noon

		Unstandardized Coefficients		Standardized Coefficients		
		---		------------------------------	T	Sig.
Model		B	Std. Error	Beta	B	Std. Error
1	(Constant)	30.248	3.649		8.289	0.000
		-0.260	0.242	-0.975	-1.074	0.314
		0.007	0.003	1.772	1.953	0.087

$$T = 30.248 - 0.260x + 0.007x^2$$

$$\frac{dT}{dx} = -0.260 + 0.014x$$

$$0.260 = 0.014x$$

The point of inversion is obtained when; $\frac{dT}{dx} = 0.$

$$x = \frac{0.260}{0.014}$$

$$x = 18.57cm$$

Therefore the prediction equation is;

$$T = 30.248 - 0.260x + 0.007x^2$$

In models D_2 and D_3 at 12noon, the observed values of inversion temperatures were at 35.0cm and 21.0 cm respectively, while the predicted values were at 28.23cm and 18.57cm respectively. These variations in the predictive values show that models are based on estimation theory rather than practical. The discrepancy between the observed and the predicted values could be attributed to the fact that the lagging on the drums and the seals are not 100 % efficient.

CONCLUSIONS

The research on predictive validation of inversion temperature points using curvilinear regression model equations was designed to predict temperature inversion points using the observed data. Curvilinear regressions model equations generated from the non-convective pools were significant at P = 0.05 level of significance. The model fits also showed the normal P-P plots of regression standardized residuals for the observed versus expected values. Though the model equations were significance for D_2 and D_3, at certain period of the day (12noon), the result shows that the validity of the model depends on the number of absorbing layers. The distribution of data posits that models are based on mere estimation theory rather than practical. It is anticipated that better lagging and seals could reduce the discrepancy between the observed and predicted values, hence future work should be geared in that direction.

ACKNOWLEDGEMENTS

The authors are grateful to the Department of Physics, Cross-river University of Science and Technology, Nigeria for permission to use their facilities.

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