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A Meta-Heuristic approach for Optimization of Thermal Performance of a Smooth Flat Plate Solar Air Heater

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Abstract

Teaching–Learning-Based Optimization (TLBO) is a newly and advance meta-heuristicoptimization method proposed in this paper for optimizing a set of design and operating parameters for a smooth flat plate solar air heater (SFPSAH).The result obtained from TLBO is more effective and efficient than the other optimization techniques which are consider for mechanical design optimization problems. The final results obtained from this algorithm are compared with experimental results and found to be satisfactory as far as convergence rate and computational effort.

Keywords: TLBO, Solar air heater, Thermal Performance

1. Introduction

Energy is a basic requirement for human being and also influences the economic development. The rapid depletion of fossil fuel resources forced human being for a search for non-conventional energy resources. Out of alternative energy resources, solar energy is available freely and abundance on earth in the form of radiation. Solar collectors are widely used for utilization of solar energy for various applications. Solar air heaters are simple to design and no complicated tracking mechanism is involved in it and also it is economical,by Duffie(1980). The solar air heaters are having low thermal efficiency due to two reasons: a) low thermal capacity of air and b) a low heat transfer co-efficient between the absorber plate and air flow through duct. In order to make the solar air heater more effective, their thermal efficiency needs to be improved,by Frank et. al.(2001). Thermal performance may be increased by increasing convective heat transfer coefficient. There are two way for increasing heat transfer coefficient either a) increase the area of absorbing surface by using fins or b) create the turbulence on the heat transferring surfaces, by Frank et. al.(2001). The value of parameter effecting thermal performance of solar air heater required to be optimized and should obtained by various optimization techniques which are either stochastic or deterministic in nature,by Lewis. M.J.(1975). Various researchers attempted using different optimization techniques such as genetic algorithm (GA), particle swarm optimization (PSO),etc.Kalogirou, S.A(2004)has applied a combination of artificial neural-networks (ANNs) and genetic algorithms (GAs) to optimize a solar-energy system having flat plate collectors with an intention to maximize its life cycle savings on an industrial heating process system. Kalogirou,S.A(2006)had estimated the performance parameters of flat plate solar collectors using ANN and results obtained are compared with actual experimental values. Varun and Siddhartha (2010) used GA and Varun et al. (2011)applied stochastic iterative perturbation technique to evaluate the optimal thermal performance of flat plate solar air heater. In this work, an attempt has been made to estimate the optimal thermal performance of a smooth flat plate solar air heater (SFPSAH) with various operating parameters and also to determine the most effective parameters through TBLO technique. This work helps to find out that how actual experimental set-up is far away from the optimized set of crucial parameters. The experimental set-up used in this study for validation of the results is shown in Figure. 1.

2 Teaching–Learning-based Optimization Theory

Raoet. al (2011) recently proposed a teaching–learning-based optimization algorithm which is based on the effect of influence of a teacher on learners output in a class. In this algorithm, a group of learners are considered as population and different offered subjects to the learners are considered as different design parameters and a learner's result is analogous to the 'fitness' value for the optimization problem. The teacher is considered as the best solution in the entire population, byRaoet. al (2011) and Repinsek(2012).

The working of TLBO algorithm is divided into two parts, 'Teacher phase' and 'Learner phase'. Let assume two d ifferent teachers, T_1 and T_2, are teaching a subject of same content to the same merit level learners in two different classes. Figure 2 shows obtained by the learners of two different classes evaluated by the respective teachers. A curve 1 and 2 represents the marks obtained by the learners taught by teacher T_1 and T_2 respectively. Normal distributions are assumed for the obtained marks, but in actual practice it

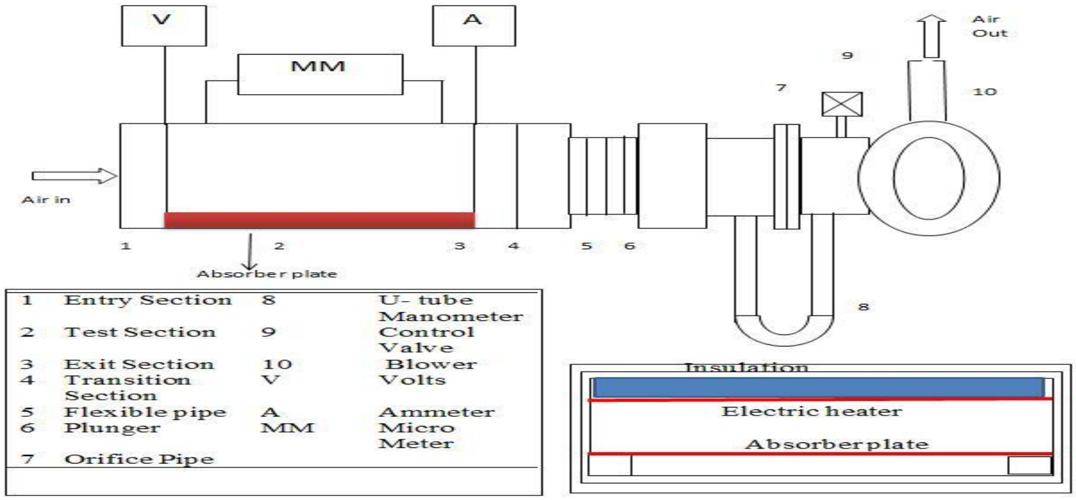


Figure 1: Schematic diagram of Experimental set-up

can have skewness. Normal distribution is defined as:

$$f(X) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-(x-\mu)^2 / 2\sigma^2\right\} \quad (1)$$

Where σ^2 is the variance, μ is the mean and x is any value of which normal distribution function is required.It is observed from Figure2 that curve-2 represents better results than curve-1 and so it concludes that teacher T_2 is better thanteacher T_1 in terms of teaching. The main difference between both the results is their mean (M_1&M_2 are respective mean for curve-1 and curve-2).This shows that a good teacher produces a better mean for the results of the learners.

Learners also learn from interaction between themselves, which also helps in their results byRaoet. al (2011 and 2012).Figure 3shows Probability density with marks obtained for learners in a classhaving mean M_A and M_B for curve-A and curve –B respectively. Teacher is considered as the most knowledgeable person in the society, so the teacher is imitated as the best learner, and this is shown by T_A in Figure 3. Learners which will increase the knowledge level of the whole class and help learners to get good marks. So, a teacher increases the mean of the class according to his or her capability.

In Figure 3, teacher T_A will make his or her effort to move mean M_A towards their own level, thereby increasing the learner's level to a new mean M_B. Teacher T_A will try to put maximum effort into teaching, but students will gain knowledge according to the quality of teaching delivered by a teacher and the quality of students present in the class, by Rao et. al (2011 and 2012).

The qualities of the students are evaluated from the mean value of the population. Teacher $T_A$puts efforts in so as to increase the quality of the students fromM_A toM_B, at which stage the students require a new teacher, of superior quality than themselves, i.e. in this case the new teacher is T_B. Hence, there will be a new curve-B with new teacher T_B. Like other nature -inspired algorithms, TLBO is also a population based.

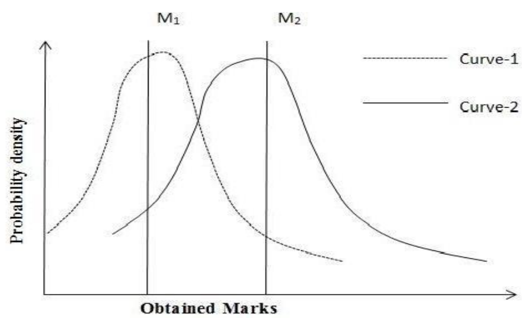


Figure2: Distribution of marks obtained by learnerstaught by two different teachers

The teacher tries to spread knowledge among the method which uses a population of solutions to proceed to the global solution, byRaoet. al (2011).

2.1. Teacher Phase

As shown in Figure 3, a good teacherinfluence mean of a class leads increment from M_A to M_B. A good teacher tries to bring his or her learners up to his or her level in terms of knowledge. But in reality this is not possible and a teacher can only improve the mean of a class up to some extent depending on the capability of the class.

This follows a random process depending on many factorsby Raoet. al (2011).

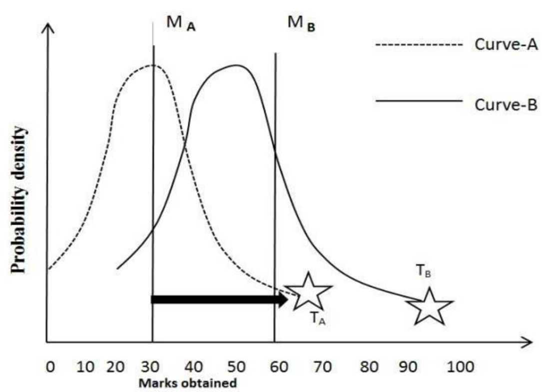


Figure 3: Model for obtained marks distribution for a group of learners

Let M_i be the mean and T_i be the teacher at any iteration i. T_i will try to move mean M_i towards its own level, so now the new mean will be T_i designated as M_{new}. The solution is updated according to the difference between the existing and the new mean given byRaoet. al.(2011).

$$Difference\_Mean = r_i\,(M_{new} - T_F M_i) \qquad (2)$$

where T_F is a teaching factor that decides the value of the mean to be changed, and r_i is a random number in the range (0, 1).

The value of T_F can be either 1 or 2 which is again a heuristic step and decided randomly with equal probability byRaoet. al.(2011).

$$T_F = round\left[1 + rand\,(0,1)\,\{2-1\}\right] \qquad (3)$$

This difference modifies the existing solution according to the following expression:

$$X_{new,i} = X_{old,i} + Difference\_Mean_i \qquad (4)$$

2.2. Learner Phase

Learners increase their knowledge by two different means: one through input from the teacher and other through interaction between themselves. A learner interacts randomly with other learners with the help of group discussions, presentations, formal ommunications, etc. A learner learns something new if the other learner has more knowledge than him or her. Learner modification is expressed by Raoet. al.(2011)and (2012)

For $i = 1; P_n$

Randomly select another learner X_j such that $i \neq j$

If $f(X_i)$ [redacted] $f(X_j)$

$$X_{new,i} = X_{old,i} + r_i (X_i - X_j) \qquad (5)$$

Else

$$X_{new,i} = X_{old,i} + r_i (X_j - X_i) \qquad (6)$$

End If

End For

Accept X_{new} if it gives a better function value.

3.1. Problem formulation

The objective function for thermal performance of SFPSAH can be proposed as:

Maximize $$\eta = F_o \left[\tau\alpha - \left(\frac{T_o - T_i}{S} \right) U_o \right] \qquad (7)$$

The different relations used for calculating overall loss coefficient (U_0), heat removal factor at outlet (F_0) and temperature rise are computed by equations:

$$U_o = \left[\frac{N}{\left(\frac{C}{T_p} \right) \left[\frac{T_p - T_a}{N + f} \right]^{0.33}} + \frac{1}{h_w} \right]^{-1} + \frac{\sigma (T_p - T_a)(T_p^2 + T_a^2)}{\left[\varepsilon_p + 0.05 N (1 - \varepsilon_p) \right]^{-1} + \left[\frac{2N + f - 1}{\varepsilon_a} \right] - N} + \frac{K_i}{t} \qquad (8)$$

Where

$$f = (1 - 0.04 h_w + 0.005 h_w^2)(1 + 0.091 N)$$

$$C = 250 \left(1 - 0.0044 (\beta - 90) \right)$$

And $h_w = 5.7 + 3.8 V_w$

$$F_o = \frac{G c_p}{U_o} \left[1 - \exp\left(\frac{-U_o F'}{G c_p} \right) \right] \qquad (9)$$

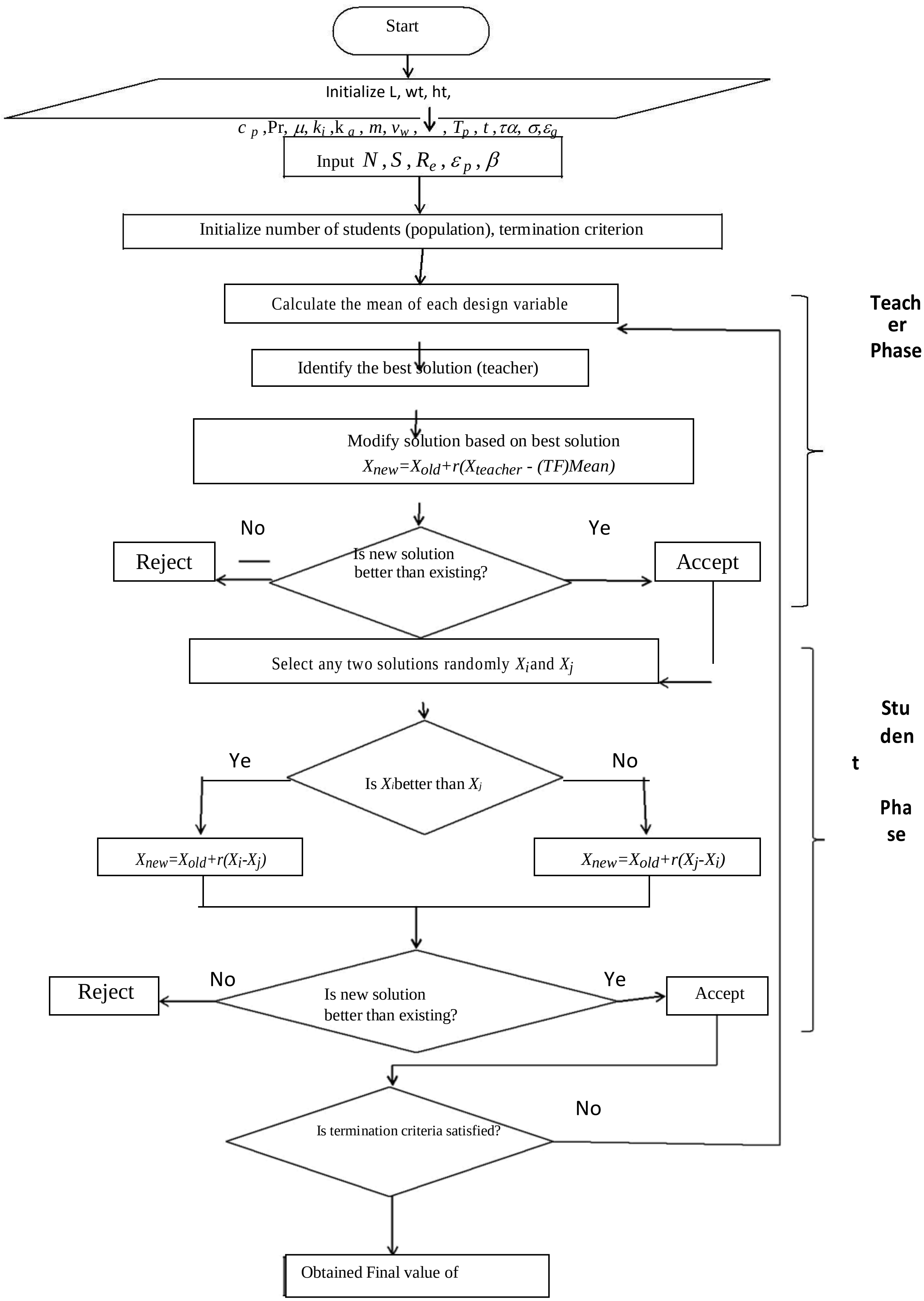
$$N_u = \frac{0.0192 P_r R_e^{0.75}}{1 + 1.22 (P_r - 2) R_e^{-1/8}} \qquad (10)$$

$$h_c = \frac{N_u c_p \mu}{P_r D_h} \qquad (11)$$

$$F_1 = \frac{h_c}{h_c + U_o}$$

$$G = m / A_c$$

$$T_o - T_i = \left[\frac{(\tau\alpha) S - U_o (T_p - T_a)}{m c_p} \right] \times A_c \qquad (12)$$


Start
Initialize L, wt, ht,
c_p, Pr, μ, k_i, k_a, m, v_w, T_p, t, $\tau\alpha$, σ, ε_g
Input $N, S, R_e, \varepsilon_p, \beta$
Initialize number of students (population), termination criterion
Calculate the mean of each design variable
Identify the best solution (teacher)
Modify solution based on best solution
$X_{new}=X_{old}+r(X_{teacher} - (TF)Mean)$
No
Ye
Reject
Is new solution better than existing?
Accept
Teacher Phase
Select any two solutions randomly X_i and X_j
Ye
Is X_i better than X_j
No
$X_{new}=X_{old}+r(X_i-X_j)$
$X_{new}=X_{old}+r(X_j-X_i)$
Student Phase
Reject
No
Is new solution better than existing?
Ye
Accept
No
Is termination criteria satisfied?
Obtained Final value of

$600 \le S \le 1000$; S is varied in steps of 200.
$2000 \le Re \le 20{,}000$; Re is varied in steps of 2000

The constraints of the problem are: $1 \le N \le 3$; N is varied in steps of 1.

Table 1: Typical values of system parameters

.Collector parameters	Values
Length (L) (mm)	1000
Width (wt) (mm)	200
Height (ht) (mm)	20
Density (kg/m^3) of air	1.117
Density of aluminium	2719
c_p of air(J/kgK)	1007
c_p of aluminium(J/kgK)	871
k_a(W/mK)	0.0262
Pr	0.72
μ	1.79×10^{-5}
k (Al)(W/mK)	202.4
k_i(W/mK)	0.037
T_a (K)	300
V_w(m/s)	1
t	0.05
τα	0.85
ε_p	0.90
ε_g	0.88

4. Results and discussion

4.1 Effect of Reynolds number on thermal performance

The increase in Reynolds number improves the turbulence effect in the flow andalso increases the mass flow rate, which enhances heat transfer rate and alsoimproves thermal performance as shown in Figure 5.The maximum value of Thermal efficiency comes out to be 61.75%, 69.95% and 79.94% respectively for three different cases as shown in table 4, 5 and 6 respectively. The TBLO approach is capable for generating the optimized set of values for practical solution for obtaining optimized thermal performance.

4.2 Effect of number of glass plates on thermal performance

The thermal performance of an SFPSAH can be also

Table 2.Set of optimised result for (N=1, v=1 m/sec and S=600 W/m^2)

Sl no	R_e	β	ε_p	$T_o - T_i$	η_{th}
1	2000	36.95	0.90	41.54	21.66
2	4000	23.72	0.94	35.67	30.14
3	6000	43.35	0.91	29.38	37.56
4	8000	43.66	0.93	21.38	42.83
5	10000	39.06	0.85	15.49	47.56
6	12000	46.33	0.90	13.34	51.36
7	14000	39.47	0.85	12.16	54.51
8	16000	21.69	0.85	11.43	57.61
9	18000	30.28	0.90	10.55	59.68
10	20000	22.65	0.85	09.44	61.75

Table 3.Set of optimised result for (N=2, v=1 m/sec and S=600 W/m^2)

Sl no	R_e	β	ε_p	$T_o - T_i$	η_{th}
1	2000	28.84	0.86	42.76	25.67
2	4000	43.80	0.90	34.06	36.95
3	6000	61.60	0.94	27.87	44.11
4	8000	38.72	0.91	21.15	49.09
5	10000	30.80	0.91	17.73	53.69
6	12000	61.01	0.89	15.21	57.43
7	14000	20.74	0.94	13.61	60.69
8	16000	15.64	0.87	12.67	63.82
9	18000	56.45	0.85	11.02	66.87
10	20000	55.32	0.85	10.26	69.95

4.3 Effect of solar radiation intensity on thermal performance

The thermal performance of SFPSAH can be also improved by decreasing top loss coefficient. The increase in solar radiation intensity leads the increase in plate mean temperature and also increase in top loss coefficient. Therefore, thermal performance decreases with increase in solar radiation intensity to improve by using more number of glass cover plates (N) as shown in Figure 5, but it makes system more complex and also increases manufacturing cost. Three different values of N are and same value of solar irradiance are considered, it was observed that thermal efficiency is maximum for three glass cover plate at Re equal to 20,000.The range for thermal performance for different validation

4.4 Validation of TLBO algorithm with Experimental data and PSO

The results obtained from the TBLO algorithm are tested with actual experimental data and PSO algorithm byVarun and Siddhartha (2012) for assuring its accuracy. When the algorithm was executed, it was number of glass cover plates with considered cases are found that the shown in Table 3, 4and 5 respectively.

Table 4.Set of optimised result for (N=3, v=1 m/sec and S=600 W/m2)

Sl no	Re	□	□	p	To □ Ti□th
1	2000	39.81	0.90	44.57	30.65
2	4000	27.96	0.92	34.51	42.93
3	6000	63.14	0.85	29.70	51.03
4	8000	45.06	0.85	21.92	56.22
5	10000	41.86	0.92	18.57	60.84
6	12000	52.83	0.90	15.93	64.98
7	14000	52.48	0.85	13.79	69.09
8	16000	25.12	0.89	12.52	73.06

9	18000	30.96	0.89	11.54	76.91
10	20000	19.77	0.91	10.89	79.94

values of thermal efficiency obtained from this algorithm are in good harmony with experimental thermal efficiency. TBLO algorithm takes most suitable parameters for obtaining optimized result. This proves that the proposed algorithm gives a clear idea regarding the domain of optimum set of design and operating parameters for flat plate solar air heater.

Figure 5. Variation of Thermal performance with Reynolds number (Re) for different number of glass plates at S= 600 W/m2

Conclusions

The conclusions which are derived from this work:

(1) TheTBLO algorithm was successfully proposed for finding theoptimal set of design and operating parameters at which thethermal performance of SFPSAH could be maximum.

(2) The maximum thermal efficiency based upon this algorithm was comes out to be 79.42% at N= 3, S =600 W/m2, Re =20000, v = 1 m/s, □ =19.77, □□p =0.91, To □ Ti =10.89 K.

(3) The algorithm helps to a researcher to explore their design and operating variables for attainment of maximum thermal efficiency of SFPSAH.

(4) The different set of parameters utilized to validate the algorithm is in good harmony with experimental results and other the algorithm also.

Nomenclature

Ap	Area of absorber plate (m2)
Ac	Cross-sectional area of duct (m2)
Dh	Hydraulic diameter (m)
Fo	Heat removal factor referred to outlet temperature
G	Mass velocity (Kg/sm2)
h	convective heat transfer coefficient(W/m2K)
Vw	Wind velocity (m/sec)
hw	wind convection coefficient(W/m2K)
S	Solar radiation (W/m2)
m	mass flow rate of air(Kg/sec)
N	number of glass cover
Pr	Prandtl number
Re	Reynolds number
t	Thickness of insulating material(m)
T a	Ambient temperature of air (K)
T i	Inlet temperature of air (K)
T o	outlet temperature of air (K)
T p	Temperature of absorber plate (K)
Uo	overall heat loss coefficient (W/m2K)
Ka	Thermal conductivity of air (W/mK)
Ki	Thermal conductivity of insulating material (W/mK)

Greek Alphabet: c p - Specific heat of air (J/kgK), p - Emissivity of plate , g - Emissivity of glass ,   - Transmittance-absorptance, - Tilt Angle -Thermal efficiency

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