Optimization of the Thermal Performance of the Solar Water Heater (SWH) Using Stochastic Technique

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Abstract- The efficiency of Solar Water Collector (SWH) is low and in order to increase its thermal performances, various optimization techniques were used. In this paper, a stochastic method (Genetic Algorithm (GA)) was adopted to increase the efficiency of the active SWH under various climatic conditions and for various operating parameters. The optimization model was introducing a lot of objectives in order to evaluate the optimality of the SWH. For the dynamic Reynolds number, solar radiation intensity and ambient temperature, different values of plate emissivity, a different number of the glass cover and velocity of air, the thermal performance were obtained and it is compared with the experimental results. It is established by the studies carried out based upon this algorithm that the maximum thermal efficiency comes out to be 75, 28 %. The application of our results was applied in such application as coupling the SWH with the anaerobic digester. The goal is to support decision makers in the definition of the optimal thermal performance and of the optimal collector flat area in order to give a good compromise between the collector efficiency and the output water temperature in the country.

Keywords- Genetic algorithms Optimization; Thermal performance; Solar water heater; Thermal solar application.

1. Introduction

The systems of energy conversion based on renewable energy technologies have the potential to give an excellent energy production. Solar energy is one of the most useful forms of the renewable energy. Solar collector (water or air) are used in heating systems for the optimal and efficient utilization of solar energy. Their applications have increased significantly in countries which have a large solar potential. In an attempt to increase the thermal performance, the modern research uses various optimization techniques; many or even most real engineering problems actually do have multiple objectives, i,e., minimize or maximize the objective function, these are difficult but realistic problems [1].

Nowadays, stochastic techniques are used for the optimization of different solar energy systems. Kalogirou [2] has used a combination of artificial neural networks (ANNs) and genetic algorithms (GAs) to optimize a solar-energy system on an industrial process heat system having flat plate collectors with an intention to maximize its life cycle savings. Loomans and Visser [3] used a genetic algorithm to calculate the yield and the costs of solar hot water systems based upon technical and financial data. Varun and Siddhartha [4] Naveen Sharma [5] have used a Genetic algorithm and stochastic iterative perturbation technique to optimized the thermal performance of the solar air heater. Kulkarni et al [6] proposed a methodology to evaluate the design space for synthesis, analysis, and optimization, considering various design constraints of solar water heating systems. Heat exchangers for refrigerators are optimized by the use of the Patero method [7]. A design of air-cooled heat exchangers was optimized by combining a mix of Global Sensitivity Analysis (GSA) and Harmony Search (HS) [8]. On other hand the stochastic technic were used in many application of renewable energy, Hossain Lipu et al [18] used Neural Network Algorithm -NNA- to select the optimum results for the State of Charge Estimation of Lithium-ion Battery for Electric Vehicle Application; Mustafa Mohamadian et al [19] and Hichem Othmani [22] have used a Fuzzy logical optimization technic to develop a smart energy management system for a Hybrid Renewable System and for optimizing a Photovoltaic Pumping System respectively . In addition, an optimal sizing algorithm to obtain the capacity sizes of several components of a hybrid renewable energy system have been used by Abubakar Mas'ud [20]. Moreover, the stochastic technic applied in renewable energy application take another aspect as the prediction of the weather data , in this context, Loutfi et al [21] was generated the Horizontal Hourly Global Solar Radiation from exogenous variables by using an Artificial Neural Network in Fes (Morocco).

In the current work, the Genetic algorithm optimization technique has been adopted to estimate the optimal thermal performance with various operating parameters and the obtained results was applied in the application of heating the anaerobic digester, i.e., the results such as the thermal efficiency, the flow rate, the losses coefficient global U_L was used to estimate and sized the heat energy requirement from the anaerobic digester [17].The present work facilitates the domain of optimized values for different parameters which are decisive for ultimately finding the best performance of such a system. The various systems operating parameters used in this study are: the ambient temperature, solar radiation, flow rate, number of glass cover and velocity of air as dynamic inputs on the basis of which entire set of optimization value of parameters such as absorber temperature, top loss heat coefficient and plate tilt angle, are estimated by the genetic algorithm and finally the thermal efficiency is determined.

2. The Thermal Performance of Solar Water Heater

The thermal performance of water heater can be evaluated and predicted by using the empirical correlations for heat transfer coefficients and others parameters, i.e., overall heat loss coefficient, heat removal factor etc. A soft code program has been developed for the proposed optimization in this paper as given in the steps bellow.

Step 1: Initializing the mean absorber plate temperature by using the approximation

$$T_p = T_a = T_i$$

Step 2: using this temperature, U_t and U_L are computed using the equations 1 and 5 respectively. The top loss coefficient is computed by following the empirical formulas (Eq.(1)) of Klein [9].

$$U_t = \frac{1}{\dfrac{N}{\dfrac{C}{T_p}\left(\dfrac{T_p - T_a}{N+f}\right)^{0,33}} + \dfrac{1}{h_w}} + \frac{\sigma(T_p^2 - T_a^2)(T_p - T_a)}{\dfrac{1}{\varepsilon_p + 0,05N(1-\varepsilon_p)} + \dfrac{2N+f-1}{\varepsilon_g} - N} \qquad (1)$$

Where,

$$f = (1 - 0,04h_w + 0,0005h_w^2)(1 + 0,091N) \qquad (2)$$

$$C = 365,9\ (1 - 0,00883\beta + 0,00001298\ \beta^2) \qquad (3)$$

$$h_w = 5,87 + 3,67\,V \qquad (4)$$

Using this value of U_t, the overall loss coefficient can be determined from the Eq.5.

$$U_L = U_t + \frac{k}{e} \qquad (5)$$

Step 3: The efficiency (F') and heat removal factors (F_R) are calculated by using the value of U_L in step 2. The collector efficiency factor is calculated by the following equation [4].

$$F' = \frac{h_{cv}}{h_{cv} + U_L} \qquad (6)$$

The heat removal factor can be calculated by eq.7 [10]:

$$F_R = \frac{\dot{m}\,C_p}{A_c U_L}\left[1 - \exp\left(-\frac{A_c F' U_L}{\dot{m}\,C_P}\right)\right] \qquad (7)$$

The forced convection coefficient h_{cv} is calculated according to the empirical formulas given by Haussen and Sider-Tate [11].

For Re < 2100

- **Case 1:** Gz < 100

$$Nu = 3,66 + \frac{0,085\,Gz}{1 + 0,047\,Gz^{\frac{2}{3}}} \qquad (8)$$

- **Case 2 :** Gz > 100

$$Nu = 1,86\,Gz^{\frac{1}{3}} + 0,87(1 + 0,015\,Gz^{\frac{1}{3}}) \qquad (9)$$

For 2100 <Re < 10000

$$Nu = 0,116(\mathrm{Re}^{\frac{2}{3}} - 125)\,\mathrm{Pr}^{\frac{1}{3}}\left(1 + \frac{D}{N'\,L}\right)^{\frac{2}{3}} \qquad (10)$$

The energy produce from the collector was computed by the equation 11 [10].

$$Q_u = A_c[G(\alpha\tau) - U_L(T_p - T_a)] = \dot{m}C_p(T_0 - T_i) \qquad (11)$$

Then, the temperature rise is computed by using the equation 12.

$$\Delta T = \frac{Q_u}{\dot{m}\,C_p} \qquad (12)$$

Step 4: We use the values calculated in the steps 1, 2 and 3, i.e., removal factor, top loss coefficient U_L, heat energy Q_u

and temperature rise ΔT in order to compute the new mean plate temperature T_p [9, 10]:

$$T_p = T_a + F_R\, G\,(\alpha\tau)\left[\frac{1-F_R}{F_R U_L} + \frac{T_0 - T_i}{G(\alpha\tau)}\right] \tag{13}$$

Step 5:

- The new value compared to the previous one and if the difference is within acceptable limits, the process is stopped;
- If the difference exceeds the acceptable values, the previous value has been retained as a revised value.

Step 6: In the end, the mean plate temperature has been calculated from the iterative procedure, the thermal performance of SWH is determined by the following equation (Eq.14) [9, 10]:

$$\eta = F_R\left[(\alpha\tau) - U_L\,\frac{(T_i - T_a)}{G}\right] \tag{14}$$

3. Genetic Algorithm

Genetic Algorithms belong to the evolutionary algorithms based on the mechanics of natural selection and use techniques inspired by evolutionary biology [12, 13]. It is a stochastic, complex and non-linear method, [14].

The conventional optimization based on the assumptions of continuity and conventional technical enumerative depends on the convergence properties, whereas GAs work with objective function information and search for an optimal parameter set to obtain an optimum value. A simple GAs cycle model of population genetics is shown in fig.1 [15].

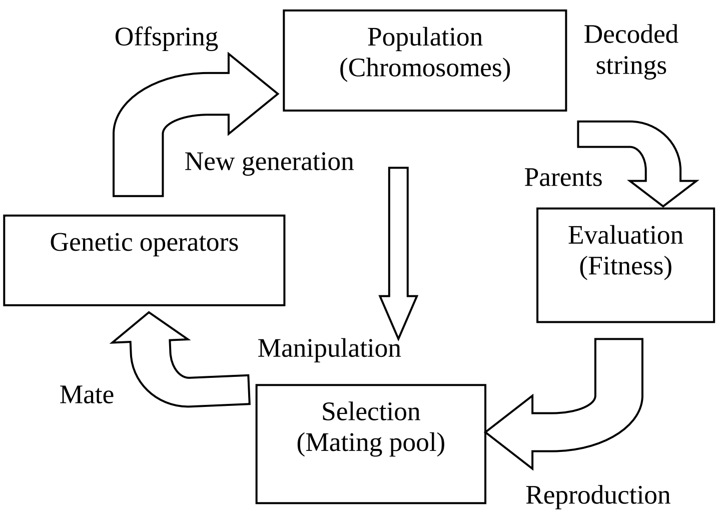

Fig.1. The genetic algorithm cycle

3.1 Detailed methodology

An optimization approach is followed in order to optimize the thermal performance of the solar collector water heater. The objective function for this problem is:

Maximize $$\eta_{th} = F_R\left[(\alpha\tau) - U_L\left(\frac{T_0 - T_i}{G}\right)\right]$$

Eq. (15)

The constraints of the problem are:

- $300 \le G \le 1000$ (W/m^2)
- $0{,}01 \le \dot{m} \le 0{,}3$ (Kg/s)
- $280 \le T_a \le 308$ (K)
- $1 \le V \le 3$ (m/s)
- $1 \le N \le 3$

The Algorithms is structured under six steps for a fixed value of ε_p, V and N. The Reynolds number is calculated based on the variation of the flow in the procedure of GAs (dynamic calculation). The latter (GAs) is developed and implemented in our soft code in order to find all optimized values and finally, the objective function was calculated using those optimized values as it's shown in fig.2.

Step 1:

Coding all parameters $[V, T_a, N\ldots]$ and we set generation counter t=0. In this step we apply the following operators:

- A roulette wheel selection, a single point crossing, and a bit mutation operator is used;
- 0,8 and 0,05 are The probabilities of crossover and mutation respectively;
- 16 chromosomes are composed the initial pool of a population.

Step 2:

An evaluation of each string in the $\left[G, T_a, \dot{m}\right]$. The objective was computed for the first string; i.e., the first substring corresponds the value equal to 800 (W/m^2); second substring 295 (K) and the third equal to 0, 1 (Kg/s), that mean the first string corresponds to a point A = [800 (W/m^2); 295 (K); 0, 1 (Kg/s)]. Now, these values are replaced by the function objective expression in order to calculate the function value, at this point, we have F(A$^{(1)}$)= 0,616; after calculating the fitness function value at the point A$^{(1)}$ we used this value obtained in the reproduction operation. In the same way, we evaluated and calculated fitness values for other strings.

Step 3 (selection operation):

Roulette-wheel selection procedure [8] was adopted to determine the average function objective of the population. When the best strings selected, a fitness values of all strings of the population was added to obtain the **F** (mean).
Afterward, the probabilities calculation of each chain was computed by using the equation (15) and it was moved into the mating pool.

$$P = \frac{F(A)}{\sum F} \tag{16}$$

The formation of the mating pool was yielded by using the Random function. In this paper and especially in this step the same procedure has been flowed for others strings which have a poor quality.

Step 4 (Crossover operation):

The crossover operation used for the strings in the mating pool. In order to select two strings out of the random POP pool, a single point cross was used, and then these results are checked by the probabilities defined in step 1. For the clarity, the crossover site is selected by creating a random number between 0 to L-1. (L: String length in our case L=32 bits). At the end of this operation, the new elements chains were put in the intermediate population.

Step 5 (Mutation):

In this step, we applied mutation operator on strings of the intermediate population. For that, we flip each bit with a probability equal to 0, 05 [15] for every bit.

Step 6

The population obtained after these steps, is now the initial population (H_0).

We repeat the step before for (H_0) which is complete one genetic algorithm iteration.

The generator counter was growth to t=t+1 in purpose to go to the next step; 0,001 is the termination criterion which represent the difference between a successive value of the efficiency.

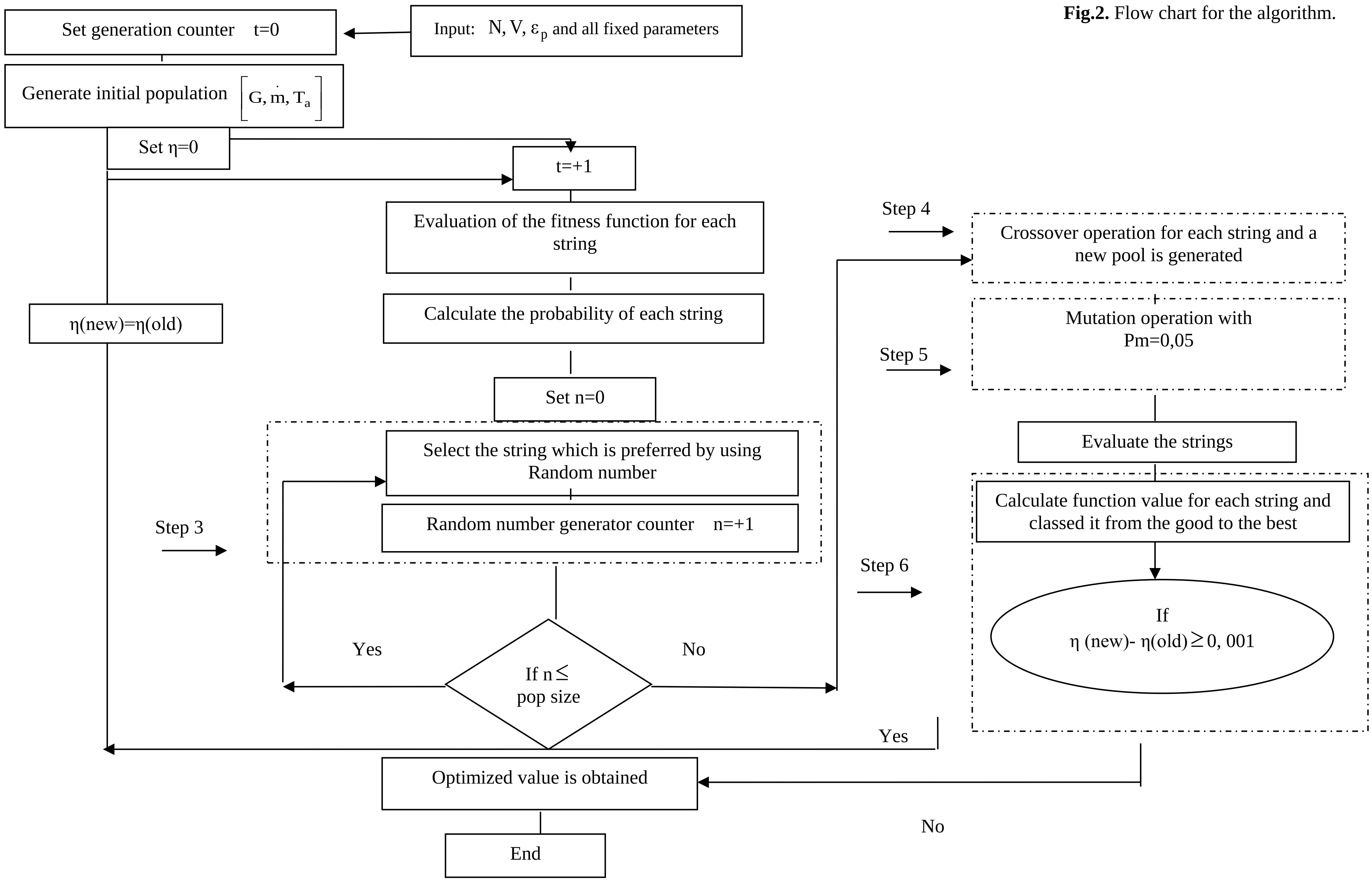

Fig.2. Flow chart for the algorithm.

4. Results and Discussion

In the current study, we start by some comparison between the experimental results (Dagdougui H. 2011) and those obtained by the Genetic algorithm in order to give an idea to what extent these Genetic algorithm results close to the experimental ones, for a fixed value of a number of glass covers and dynamic solar radiation intensity, as presented in Table 1. It should note that the experimental results are only available for the thermal efficiency of SWH for the cimparaison.

Table 1. Experiments results of Dagdougui [16] compared with the current GAs results.

Flow rate (Kg/s)	η (Experimental values) %	η (GAs values) %
0,01	38	36,86
0,02	40	38,74
0,04	56	57,44
0,06	59	62,34

4.1 Effect of Reynolds number on thermal performance

From the results obtained by Genetic algorithm method as shown in Fig.3, we understood that increase in Reynolds number offset by a rise in heat transfer. i.e., increasing the Reynolds number increases the turbulence in the flow which leads to higher heat transfer and consequently gives a higher thermal performance.

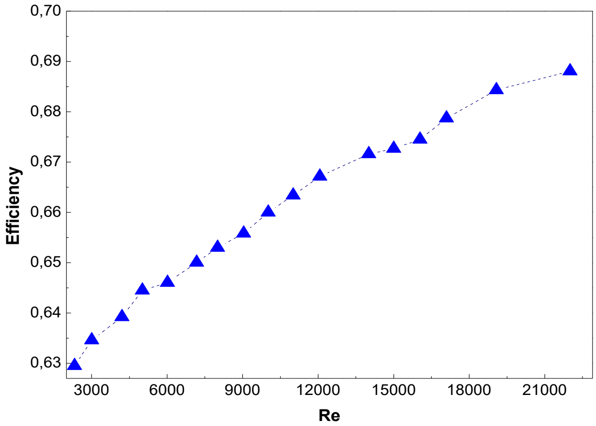

Fig.3. Variation of thermal performance with Reynolds Number.

The thermal performance ranges from 62,152 % to 69,83 % as the Reynolds number varies from 1800 to 22000 and for; $\varepsilon_p = 0{,}1$; $V = 1\,m/s$; $\beta = 33°$, T_a ranges from 283 K to 303 K and solar radiation intensity is lying between 300 and 1000 W/m^2,i.e, the variation of Reynolds number is calculated from the variation of the flow rate as mentioned previously. Similarly, the thermal performance ranges from 64, 831 % to 72, 89 % and between 63, 79 % to 70,494 % for three and two glass cover respectively as shown in fig.3.

4.2 *Effect of number glass covers on thermal*

Using a number of the glass cover increases the thermal performance of the flat plate solar collector water heater as shown in fig.4 but, at the same time increase, the cost of the system for sure and the system. In this present work, three sets of the glass cover were used (N=1, 2 , 3) and it has been found that with the same value (fixed values) of ε_p, β, V and for the variation of the Reynolds number (Re), the ambient temperature and the solar radiation intensity, the thermal efficiency increase proportionally to the variation of the number of the glass cover as exposed in fig.4.

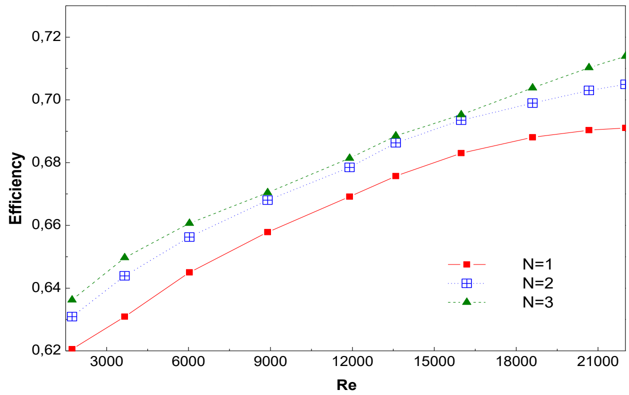

Fig.4. Variation of thermal performance for a different number of the glass cover.

The thermal performance for three glass cover varies from 63,62 %($N=3$; $\varepsilon_p = 0{,}1$; β=33°; $V = 1\,m/s$ and $Re = 1800$) to 72 % ($N=3$; $\varepsilon_p = 0{,}1$; β=33°; $Re = 22000$). Similarly for two glass cover, the thermal efficiency varies from 62, 8 % ($N=2$; $\varepsilon_p = 0{,}1$; β=33°; $V = 1\,m/s$ and $Re = 1800$) to 70,5 % ($N=2$; $\varepsilon_p = 0{,}1$; β=33°; $V = 1\,m/s$ and $Re = 22000$)) and for a single glass cover 61,7 % ($N=1$; $\varepsilon_p = 0{,}1$; β=33°; $V = 1\,m/s$ and $Re = 1800$) to 69 % ($N=1$; $\varepsilon_p = 0{,}1$; β=33°; $V = 1\,m/s$ and $Re = 22000$) .

4.3 *Effect of emissivity on thermal performance*

In order to maximize our function objective (Eq.14) as a goal of the current work, the effect of emissivity of absorber on top heat loss coefficient U_L (Eq.1) has been treated as it is shown in fig.5 and indirectly effect on thermal efficiency as illustrated in Table 2.

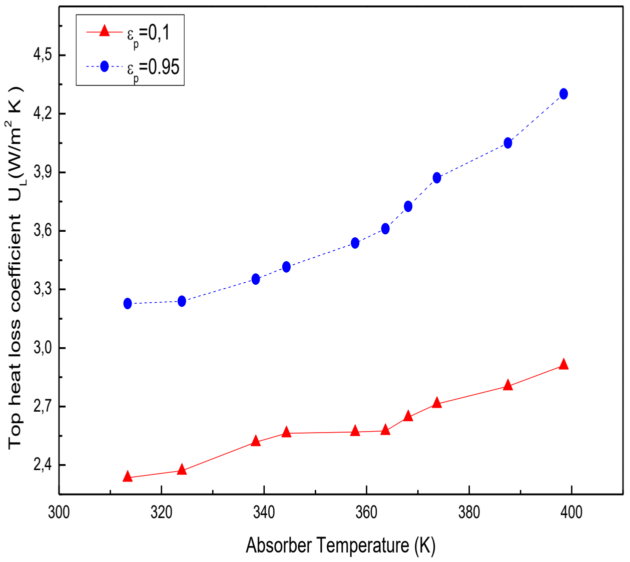

Fig.5. Top heat loss coefficient against the emissivity of the absorber for single glass cover.

The thermal performance depends on different design component. This part of study concentrates on the effect of the absorber emissivity on heat transfer process. The fig.5 displays the top heat loss coefficient as a function of the absorber temperature (Eeq.13) for two cases ($\varepsilon_p = 0,1$ and $\varepsilon_p = 0,95$). The simulations have been performed for $N=1$, β=33°; $V = 1$ m/s and 283 K< T_a < 303 K, at given values of the absorber emissivity 0, 1 and 0, 95 as minimum and maximum respectively.

Table 2. Set of optimization results of the thermal performance at different absorber emissivity.

S. no.	$\eta(\varepsilon_p = 0{,}1)$	$\eta(\varepsilon_p = 0{,}95)$
1	0,6205	0,6155
2	0,63092	0,62738
3	0,645	0,6384
4	0,65781	0,63946
5	0,66913	0,64052
6	0,67568	0,64255
7	0,68305	0,64988
8	0,68807	0,65194
9	0,69035	0,66633

The heat losses are diminished for a selective absorber which has $\varepsilon_p = 0{,}1$, this kind of cover re-emit a small quantity of solar radiation incident like it's shown in the figure, on contrary for $\varepsilon_p = 0{,}95$ which gives a higher value of U_L.

The higher value of U_L indicating the increase of coefficient of radiation between the glass cover and absorber and this means bigger heat losses from the collector and automatically effect on thermal performance as shown in tab.2. The thermal efficiency ranges from 62,05 % for $\varepsilon_p = 0{,}1$; $N=1$; β=33°; $V = 1$ (m/s) and, U_L =2, 29 to 3,1 (W/m^2.K) to 69 % and from 61,55 % to 66,63 % for $\varepsilon_p = 0{,}95$; $N=1$; β=33°; V= 1 m/s and, U_L =3, 2 to 4, 5 (W/m^2.K).

4.4 Effect of solar radiation intensity on thermal performance

In this part, the sets of optimizing results for a fixed number of the glass cover and for the fixed value of solar radiation has been found, i.e., the optimal values have been determined which corresponding that solar collector water heater worked in the optimal operating parameters. Due to increase in mean plate temperature, the top loss coefficient of SWH also increases. The detailed set of parameters for various numbers of glass plates, solar radiation intensity, absorber temperature and top heat loss coefficient has been given in Tables 3–8. In fact, it was fixed the glass cover number and the absorber parameter in order to show and to prove the effect of the solar radiation on thermal performance of the heater system, i.e., all parameter are generated dynamically when the algorithm was compiled. As illustrated in the tables 3 and 4, the effect of the solar radiation on the efficiency of the system, which is a proportional relationship, i.e., when the solar radiation equal to 300 W/m2 the efficiency reaches a maximum of
64, 7%, on the contrary, it is attained a value of 66.4% when the irradiance is 1000 W/m^2. Also, the solar radiation affected (increase) on the top loss coefficient and consequently affect (maximize) on the thermal performance, whereas the efficiency reaches 70% when irradiance attain 1000 w/m2 on the contrary when it equal to 300 it's reached an efficiency equal to 66% for the same value of the all other parameters as shown in the tables 5 and 6. In addition, the tables 7 and 8 confirmed that the solar irradiance affects strongly on the efficiency of the solar thermal heater, whereas the maximum efficiency reached is 75 % corresponding to 1000 W/m^2.

Table 3. Set of optimizing results for $N=1; \varepsilon_p = 0{,}1$; $G = 300$ W/m^2.

S.no	Flow rate (kg/s)	T_p (K)	U_t (W/m^2.K)	η_{GA} %
1	0,03632	374,35346	4,10399	56,83325
2	0,06808	355,24742	4,05526	58,45057
3	0,09756	344,24831	3,42700	60,58292
4	0,12707	327,53059	2,90944	62,90831
5	0,18800	303,40718	2,73322	64,76310

Table 4. Set of optimizing results for $N = 1$; $\varepsilon_p = 0{,}1$; $G = 1000$ W/m^2.

S.no	Flow rate (kg/s)	T_p (K)	U_t (W/m^2.K)	η_{GA} %
1	0,03632	395,58927	2,90944	57,27501
2	0,06808	373,12681	2,67853	59,63453
3	0,09756	353,76056	2,50280	62,24576
4	0,12707	330,37918	2,34082	64,53143
5	0,18840	305,14723	2,29351	66,42987

Table 5. Set of optimizing results for $N = 2$; $\varepsilon_p = 0{,}1$; $G = 300$ W/m^2.

S.no	Flow rate (kg/s)	T_p (K)	U_t (W/m^2.K)	η_{GA} %
1	0,03632	355,01185	4,22339	57,904856
2	0,06808	349,68772	4,12015	59,513972
3	0,09756	335,34244	4,03945	61,845322
4	0,12707	321,85504	3,79450	65,760509
5	0,1884	301,89920	3,79135	66,663575

Table 6. Set of optimizing results for $N = 2$; $\varepsilon_p = 0{,}1$; $V = 1$ m/s; $G = 1000$ W/m^2.

S.no	Flow rate (kg/s)	T_p (K)	U_t (W/m^2.K)	η_{GA} %
	0,03632	397,88174	4,30013	60,85076
2	0,06808	389,49482	4,25495	62,57328
3	0,09756	378,69812	4,19342	67,45704
4	0,12707	365,36673	4,17194	68,53836
5	0,18840	346,99716	4,16654	70,18927

Table 7. Set of optimizing results for $N = 3$; $\varepsilon_p = 0{,}1$; $V = 1$ m/s; $G = 300$ W/m^2.

S.no	Flow rate (kg/s)	T_p (K)	U_t (W/m^2.K)	η_{GA} %
1	0,03632	394,35083	5,61156	61,19828
2	0,06808	383,72111	5,48376	63,10866
3	0,09756	368,14448	5,15152	64,73418
4	0,12707	351,82865	5,02469	67,46539
5	0,18840	326,93206	4,95719	68,26124

Table 8. Set of optimizing results for $N = 3$; $\varepsilon_p = 0{,}1$; $V = 1$ m/s; $G = 1000$ W/m^2.

S.no	Flow rate (kg/s)	T_p (K)	U_t (W/m^2.K)	η_{GA} %
1	0,03632	401,91394	5,62062	61,85247
2	0,06808	383,81288	5,59284	65,78659
3	0,09756	368,02452	5,55207	69,95290
4	0,12707	325,15323	5,47580	72,13665
5	0,18840	318,42819	5,30190	75,28984

5. Conclusion

The Following conclusions are derived from the present work:

- The current study exploits the Genetic algorithm potential for finding the optimal results for an excellent thermal performance of solar water heater.
- It is established by the studies carried out based up on this algorithm that the maximum thermal efficiency comes out to be 75, 28 % at $N = 3$; $G = 1000$ W/m^2; $V = 1$ m/s and $\varepsilon_p = 0{,}1$.
- The algorithm developed is able to give a clear idea to research to explore their design and operating variables for the attainment of the maximum thermal efficiency of the current system.
- The current results have been used in the work of [17] which was exploited these optimal results to design and sizing the heat solar system of the anaerobic digester.

For the future work, the application of our results will be applied in such application as heating building, heating a UASB bio-digester by solar water heater under TRNSYS platform, i.e., coupled our program as an optimization function in TRNSYS software for designing and sizing a solar water heater.

Abbreviations

A_c: Area of absorber plate (m^2)
C_p Specific heat of air (J/kg K)
D: Hydraulic diameter of the duct (m)
e: The thickness of insulating material (m)
F_R: Heat removal factor (dimensionless)
F': Collector efficiency factor (dimensionless)
G: irradiance (W/m^2)
Gz: Graetz number (dimensionless)
h_{cv}: Water convective heat coefficient (W/m^2 K)
h_w: Wind convection coefficient (W/m^2 K)
T_a: Ambient temperature(°C)
T_i: The inlet temperature of water (°C)
T_0: The outlet temperature of water (°C)
K: The thermal conductivity of water (W/m.K)
K_i: The thermal conductivity of insulation material(W/m.K)
$\dot{m}$:Mass flow rate of water (Kg/s)
N: number of glass covers (dimensionless)
N_u: Nusselt number
N‘: number of absorbers tubes
Q_u: Useful energy (W)
P_r: Prandtl number (dimensionless)
Re: Reynolds number (dimensionless)
U_L: overall loss coefficient (W/m^2 K)
U_t: top loss coefficient (W/m^2 K)

V: the velocity of air (m/s)
$\alpha\tau$: transmittance–absorptance product
η : thermal performance (dimensionless)
ε_g : emittance of glass cover (dimensionless)
ε_p : emittance of the plate absorber (dimensionless)
SIPT : Stochastic Iterative Perturbation Technique
GA : Genetic Algorithm
SHW : Solar Heater water
ANNs : Artificial Neural Networks

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