USE OF GENETIC ALGORITHMS FOR THE OPTIMAL DESIGN OF FLAT PLATE SOLAR COLLECTORS

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Abstract - The performance of a flat plate collector depends on the collector efficiency factor (F′). The value of the collector efficiency factor depends on a number of parameters like the riser pipe diameter, the distance between the riser pipes, the type of materials of construction and thickness, and many others. For a collector of fixed width the efficiency increases by increasing the number of riser tubes. However, by increasing the number of tubes the cost of the collector is also increased. Therefore the objective of the work presented here is to find the optimum number of tubes. For this purpose a genetic algorithm is used which is inspired by the way living organisms adapt to the harsh realities of life in a hostile world. A genetic algorithm is an optimum search technique based on the concepts of natural selection and survival of the fittest. The cost of the extra tubes considered is compared against the extra value of the energy collected by considering average weather conditions for 20 years (mean life of the system) and two types of conventional sources of energy i.e., light fuel oil (LFO) and electricity. The results show that a smaller number of tubes than the traditional number (10-12) have been obtained for the case where light fuel oil is considered and the number is insensitive to the pipe size, whereas an increased number is obtained in the case where electricity is considered. This is because electricity is 3.5 times more expensive than LFO.

1. INTRODUCTION

Genetic algorithms are inspired by the way living organisms adapt to the harsh realities of life in a hostile world, i.e., by evolution and inheritance. The algorithm imitates the process the evolution of population by selecting only fit individuals for reproduction. Therefore, a genetic algorithm is an optimum search technique based on the concepts of natural selection and survival of the fittest. It works with a fixed-size population of possible solutions of a problem, called individuals, which are evolving in time. A genetic algorithm utilizes three principal genetic operators: selection, crossover, and mutation.

During each step (called a generation) in the reproduction process, the individuals in the current generation are evaluated by a fitness function value, which is a measure of how well the individual solves the problem. Then each individual is reproduced in proportion to its fitness: the higher the fitness, the higher its chance to participate in mating (crossover) and to produce an offspring. A small number of newborn offspring undergo the action of the mutation operator. After many generations, only those individuals who have the best genetics (from the point of view of the fitness function) survive. The individuals that emerge from this 'survival of the fittest' process are the ones that represent the optimal solution to the problem specified by the fitness function and the constraints. More details on genetic algorithms are given later in this paper.

A number of researchers have used genetic algorithms as optimisation tools of solar energy systems.

Genetic algorithms have been used as a design support tool by Loomans and Visser (2002) for the optimization of large hot water systems. The tool calculates the yield and the costs of solar hot water systems based on technical and financial data of the system components. The genetic algorithm allows for the optimization of separate variables as the collector type, the number of collectors, the heat storage capacity and the collector heat exchanger area.

Kalogirou (2002) used also genetic algorithms together with a neural network for the optimization of the design of solar energy systems. The method is presented by means of an example referring to an industrial process heat system. The genetic algorithm is used to determine the optimum values of collector area and the storage tank size of the system which minimize the solar energy price. According to the author the solution reached is more accurate than the traditional trial and error method and the design time is reduced substantially.

Krause *et al.* (2002) present a study in which two solar domestic hot water systems in Germany have been optimized by employing validated TRNSYS models in combination with genetic algorithms. Three different optimization procedures are presented. The first concerns the planning phase. The second one concerns the operation of the systems and should be carried out after about one year of data is collected. The third one examines the daily performance considering predictions of weather and hot water consumption and actual temperature level in the storage tank.

The objective of the present work is to determine the optimum number of the collector riser tubes. This is a complex problem because such decision depends on many factors which are interrelated between themselves. For this purpose an evolution strategy based on genetic algorithms is used to determine the optimum solution.

2. ANALYSIS

In this section various relations that are required in order to determine the useful energy collected and the interaction of the various constructional parameters on the performance of a collector are presented.

The useful energy collected from a collector can be obtained from the following formula:

$$Q_u = AF_R\left[I(\tau\alpha) - U_L\left(T_i - T_a\right)\right] \tag{1}$$

where F_R is the heat removal factor given by:

$$F_R = \frac{mc_p}{AU_L}\left(1 - Exp\left[\frac{U_L F' A}{mc_p}\right]\right) \tag{2}$$

In Eq. (2) F′ is the collector efficiency factor which is calculated by considering the temperature distribution between two pipes of the collector absorber and by assuming that the temperature gradient in the flow direction is negligible (Duffie and Beckman, 1991). This analysis can be performed by considering the sheet tube configuration shown in Fig. 1, where the distance between the tubes is W, the tube diameter is D, and the sheet thickness is δ. As the sheet metal is usually made from copper or aluminum which are good conductors of heat, the temperature gradient through the sheet is negligible, therefore the region between the centerline separating the tubes and the tube base can be considered as a classical fin problem. By following this analysis the equation to estimate F′ is given by:

$$F' = \frac{\dfrac{1}{U_L}}{W\left[\dfrac{1}{U_L\left[D + (W - D)F\right]} + \dfrac{1}{C_b} + \dfrac{1}{\pi D_i h_{fi}}\right]} \tag{3}$$

The collector overall heat loss coefficient can be obtained from:

$$U_L = U_t + U_b + U_e \tag{4}$$

i.e., it is the heat transfer resistance from the absorber plate to the ambient air.

A physical interpretation of F′is that it represents the ratio of the actual useful energy gain to the useful energy gain that would result if the collector absorbing surface had been at the local fluid temperature. It should be noted that the denominator of equation (3) is the heat transfer resistance from the fluid to the ambient air. This resistance can be represented as $1/U_o$. Therefore another interpretation of F′ is:

$$F' = \frac{U_o}{U_L} \tag{5}$$

In Equation (3), C_b is the bond conductance which can be estimated from knowledge of the bond thermal conductivity k_b, the average bond thickness γ, and the bond width b. The bond conductance on a per unit length basis is given by:

$$C_b = \frac{k_b b}{\gamma} \tag{6}$$

The bond conductance can be very important in accurately describing the collector performance and generally it is necessary to have good metal-to-metal contact so that the bond conductance is greater that 30 W/mK and preferably the tube should be welded to the fin.

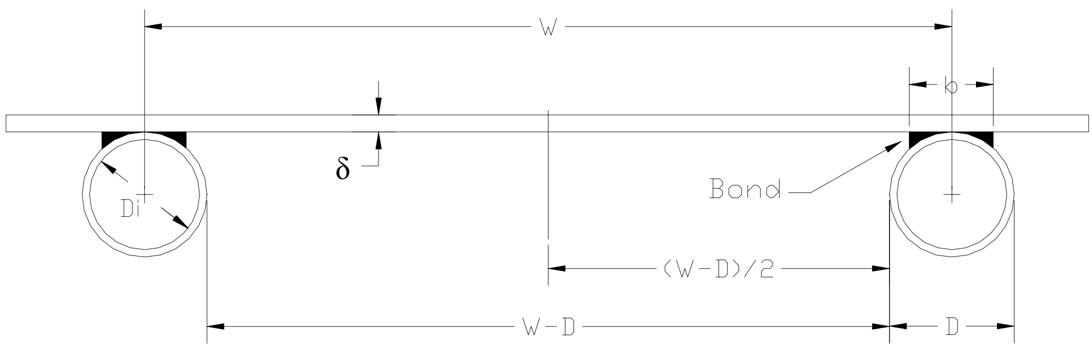

Fig. 1 Flat-plate sheet and tube configuration

Factor F in Eq. (3) is the standard fin efficiency for straight fins with rectangular profile, obtained from:

$$F = \frac{\tanh\left[n(W-D)/2\right]}{n(W-D)/2} \tag{7}$$

where n is given by:

$$n = \sqrt{\frac{U_L}{k\delta}} \tag{8}$$

The collector efficiency factor is essentially a constant factor for any collector design and fluid flow rate. The ratio of U_L to C_b, the ratio of U_L to h_{fi}, and the fin efficiency F are the only variables appearing in Eq. (3) that may be functions of temperature. For most collector designs F is the most important of these variables in determining F′. The factor F′ is a function of U_L and h_{fi}, each of which has some temperature dependence, but it is not a strong function of temperature. Additionally, the collector efficiency factor decreases with increased tube center-to-center distances and increases with increases in both material thicknesses and thermal conductivity. Increasing the overall loss coefficient decreases F′ while increasing the fluid-tube heat transfer coefficient increases F′.

Therefore it is obvious from the above analysis that by increasing F′ more energy can be intercepted by the collector. By keeping all other factors constant increase of F′ can be obtained by decreasing W. However, decrease in W means increased number of tubes and therefore extra cost would be required for the construction of the collector. The optimum is estimated here by using a genetic algorithm to maximise the energy savings, i.e., the extra energy collected against the extra cost of the collector (resulting from the increased number of riser tubes).

3. GENETIC ALGORITHM

The genetic algorithm (GA) is a model of machine learning, which derives its behavior from a representation of the processes of evolution in nature. This is done by the creation within a machine/computer of a population of individuals represented by chromosomes. Essentially these are a set of character strings that are analogous to the chromosomes that we see in the DNA of human beings. The individuals in the population then go through a process of evolution.

It should be noted that evolution as occurring in nature or elsewhere is not a purposive or directed process, i.e., there is no evidence to support the assertion that the goal of evolution is to produce Mankind. Indeed, the processes of nature seem to end to different individuals competing for resources in the environment. Some are better than others are, those that are better are more likely to survive and propagate their genetic material.

In nature, the encoding for the genetic information is done in a way that admits asexual reproduction typically results in offspring that are genetically identical to the parent. Sexual reproduction allows the creation of genetically radically different offspring that are still of the same general species.

In an over simplified consideration, at the molecular level what happens is that a pair of chromosomes bump into one another, exchange chunks of genetic information and drift apart. This is the recombination operation, which in GAs is generally referred to as crossover because of the way that genetic material crosses over from one chromosome to another.

The crossover operation happens in an environment where the selection of who gets to mate is a function of the fitness of the individual, i.e. how good the individual is at competing in its environment. Some GAs use a simple function of the fitness measure to select individuals (probabilistically) to undergo genetic operations such as crossover or asexual reproduction, i.e., the propagation of genetic material remains unaltered. This is fitness - proportionate selection. Other implementations use a model in which certain randomly selected individuals in a subgroup compete and the fittest is selected. This is called tournament selection. The two processes that most contribute to evolution are crossover and fitness based selection/reproduction. Mutation also plays a role in this process.

GAs are used for a number of different application areas. An example of this would be multidimensional optimization problems in which the character string of the chromosome can be used to encode the values for the different parameters being optimized.

In practice, therefore, this genetic model of computation can be implemented by having arrays of bits or characters to represent the chromosomes. Simple bit manipulation operations allow the implementation of crossover, mutation and other operations.

When the GA is executed, it is usually done in a manner that involves the following cycle (Zalzala and Fleming, 1997). Evaluate the fitness of all of the individuals in the population. Create a new population by performing operations such as crossover, fitness-proportionate reproduction and mutation on the individuals whose fitness has just been measured. Discard the old population and iterate using the new population. One iteration of this loop is referred to as a generation. The structure of the standard genetic algorithm is shown in Fig. 2.

Genetic Algorithm

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Begin (1)
        t = 0 [start with an initial time]
        Initialize Population P(t) [initialize a usually random population of individuals]
        Evaluate fitness of Population P(t) [evaluate fitness of all individuals in population]
        While (Generations < Total Number) do begin (2)
              t = t + 1 [increase the time counter]
              Select Population P(t) out of Population P(t-1) [select subpopulation for offspring production]
              Apply Crossover on Population P(t)
              Apply Mutation on Population P(t)
              Evaluate fitness of Population P(t) [evaluate new fitness of population]
        end (2)
end (1)
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Fig. 2 The structure of standard genetic algorithm

With reference to Fig.2, in each generation individuals are selected for reproduction according to their performance with respect to the fitness function. In essence, selection gives a higher chance of survival to better individuals. Subsequently genetic operations are applied in order to form new and possibly better offspring. The algorithm is terminated either after a certain number of generations or when the optimal solution has been found. More details on genetic algorithms can be found in Goldberg (1989).

The first generation (generation 0) of this process operates on a population of randomly generated individuals. From there on, the genetic operations, in concert with the fitness measure, operate to improve the population.

Genetic algorithms (GA) are suitable for finding the optimum solution in problems were a fitness function is present. Genetic algorithms use a "fitness" measure to determine which of the individuals in the population survive and reproduce. Thus, survival of the fittest causes good solutions to progress. A genetic algorithm works by selective breeding of a population of "individuals", each of which could be a potential solution to the problem. The genetic algorithm is seeking to breed an individual, which either maximizes, minimizes or it is focused on a particular solution of a problem. In this case, the genetic algorithm is seeking to breed an individual that maximizes the energy saving resulting from the number of riser pipes used.

The larger the breeding pool size, the greater the potential of it producing a better individual. However, the fitness value produced by every individual must be compared with all other fitness values of all the other individuals on every reproductive cycle, so larger breeding pools take longer time. After testing all of the individuals in the pool, a new "generation" of individuals is produced for testing.

A genetic algorithm is not gradient based, and uses an implicitly parallel sampling of the solutions space. The population approach and multiple sampling means that it is less subject to becoming trapped to local minima than traditional direct approaches, and can navigate a large solution space with a highly efficient number of samples. Although not guaranteed to provide the globally optimum solution, GAs have been shown to be highly efficient at reaching a very near optimum solution in a computationally efficient manner.

During the setting up of the GA the user has to specify the adjustable chromosomes, i.e. the parameters that would be modified during evolution to obtain the maximum value of the fitness function. In this work, only one is used, i.e. the number of riser tubes. Additionally the user has to specify the range of this parameter called constraint. In the present work, this constraint is equal to 2-15 pipes in step of 1 pipe. The cost of the extra tubes considered is compared against the extra value of the energy collected by considering average weather conditions for 20 years (mean life of the system). The energy collected is estimated by using the various equations presented in section 2. The amount of the extra energy collected is transferred into monetary value by considering as conventional source of energy both light fuel oil and electricity. By subtracting the riser tube cost from the energy price the energy saving can be estimated and this value is the fitness function which is maximised.

The genetic algorithm parameters used in the present work are:

- Population size=50

Population size is the size of the genetic breeding pool, i.e., the number of individuals contained in the pool. If this parameter is set to a low value, there would not be enough different kinds of individuals to solve the problem satisfactorily. On the other hand, if there are too many in the population, a good solution will take longer to be found because the fitness function must be calculated for every individual in every generation.

- Crossover rate=90%

Crossover rate determines the probability that the crossover operator will be applied to a particular chromosome during a generation.

- Mutation rate=1%

Mutation rate determines the probability that the mutation operator will be applied to a particular chromosome during a generation.

- Generation gap=96%

Generation gap determines the fraction of those individuals that do not go into the next generation. It is sometimes desirable that individuals in the population be allowed to go into next generation. This is especially important if individuals selected are the most fit ones in the population.

- Chromosome type=continuous

Populations are composed of individuals, and individuals are composed of chromosomes, which are equivalent to variables. Chromosomes are composed of smaller units called genes. There are two types of chromosomes, continuous and enumerated. Continuous are implemented in the computer as binary bits. The two distinct values of a gene, 0 and 1, are called alleles. Multiple chromosomes make up the individual. Each partition is one chromosome, each binary bit is a gene, and the value of each bit (1, 0, 0, 1, 1, 0) is an allele. Enumerated chromosomes consist of genes, which can have more allele values than just 0 and 1. There are two different types of enumerated chromosomes; 'repeating genes' and 'unique genes'. Unique genes have to be used in cases that each gene is used only once and repeating genes where chromosomes can have repeating genes like 2,3,2,4,5,2,3 or even 2,2,2,2,2,2,2.

The genetic algorithm is usually stopped after best fitness remained unchanged for a number of generations or when the optimum solution is reached. In this work the genetic algorithm was stopped after best fitness remained unchanged for 75 generations.

4. RESULTS

As described above, the cost of the extra tubes considered is compared against the extra value of the energy collected by considering average weather conditions for 20 years (mean life of the system).

Relations 1 to 8 above were used together with other characteristics and economic parameters of the system in combination with a genetic algorithm program to find the optimum number of riser tube (adjustable chromosome) that maximises the energy saving of the system (fitness function). The whole model was set – up in a spreadsheet program in which the various parameters and equations (like Eqs. 1 to 8) are entered into different cells. The adjustable chromosome is also set in a different cell and the fitness function is the cell that contains an equation giving the energy savings of the system for a twenty years period. It should be noted that, the spreadsheet file described above need to be constructed once. The only changes required for different problems (different pipe size or type of fuel) would be to modify the cells with the input parameters and the cell containing the fuel price.

The input parameters are shown in Table 1 whereas the parameters estimated are $1/U_L$ (from Eq. 4), n (from Eq. 8), F (from Eq. 7), F′ (from Eq. 3), F_R (from Eq. 2), Q_u (from Eq. 1), and ΔQ_u, which is equal to Q_u-Q_{ref}, a reference useful energy estimated with N=1 (one riser pipe). Finally the energy price is estimated, according to the useful energy collected and the price of the fuel considered, and the energy saving, which is equal to the energy price minus the riser tube cost. This final relation is the fitness function which the program, seeks to maximize by changing the number of tubes (adjustable chromosome). As can be seen, although this is a relatively simple problem with only one adjustable chromosome, each variation of the chromosome causes recalculation of all the above equations in the sequence indicated. The cost of each riser tube, shown in Table 1, refers to the current price taken from local solar collector manufacturers. A fixed collector width of one meter is considered in this work. Therefore the distance W (in meters) for each number of riser tubes (N) is estimated from the following equation:

$$W = \frac{1-(ND)}{N-1} \tag{9}$$

Table 1. Input parameters

Parameter	Value
Heat loss coefficient (U_L)	8 W/m^2K
Absorber thermal conductivity (k)	385 W/mK (copper)
Absorber (fin) thickness (δ)	0.5 mm
Distance between riser tubes (W)	Estimated from number of tubes, using Eq. (9)
Riser tube outside diameter (D)	0.009, 0.012, 0.015 mm
Riser tube inside diameter (D_i)	0.008, 0.0105, 0.0135 mm
Bond conductance (C_b)	30 W/mK
Heat transfer coefficient inside absorber tube (h_{fi})	300 W/m^2K
Mass flow rate (m)	0.015 kg/s
Specific heat capacity (c_p)	4180 J/kgK (water)
Transmittance-absorptance produce (τα)	0.7
Temperature difference (ΔT) [$=T_i$-T_a]	25°C (mean value)
Solar radiation (I)	500 W/m^2 (mean value)
Cost of each riser tube (2m long)	C£3/tube

The solution reached by applying the method suggested here gives the results shown in Table 2. It should be noted that the traditional number of tubes employed is 10-12 and the usual size of pipe is 15 mm. As can be seen from the results presented in Table 2 a smaller number of tubes than the traditional number has been obtained for the case where light fuel oil is considered and the number is insensitive to the pipe size, whereas an increased number is obtained in the case where electricity is considered. This is because electricity is 3.5 times more expensive than light fuel oil. Therefore when electricity is used, as a more expensive fuel is replaced with solar energy, an increased number of tubes is found to be more viable. It should be noted that for each run of the program the optimum solution was reached in less than 15 seconds on a Pentium 400 MHz machine, which is very fast.

Table 2. Results of the optimization program

Pipe size (mm)	Optimum number of tubes	
	Electricity	Light fuel oil
9	13	7
12	12	7
15	11	7

5. CONCLUSIONS

As it is shown in this paper the performance of a flat plate collector depends on the collector efficiency factor (F′) which depends on a number of parameters like the riser pipe diameter, the distance between the riser pipes, the type of materials of construction and thickness. For a collector of fixed width the efficiency increases by increasing the number of riser tubes. However, by increasing the number of tubes the cost of the collector is also increased.

To find the optimum number of tubes a genetic algorithm is used. The cost of the extra tubes considered is compared against the extra value of the energy collected by considering average weather conditions for 20 years (mean life of the system) and two types of conventional sources of energy (light fuel oil and electricity). The solution reached by applying the method suggested here is given for both fuels and for a number of pipe sizes. As it is shown in this paper a smaller number of tubes than the traditional number (10-12) have been obtained for the case where light fuel oil is considered and the number is insensitive to the pipe size whereas an increased number of tubes is obtained in the case where electricity is considered. This is because electricity is 3.5 times more expensive than light fuel oil. Therefore when electricity is used, as a more expensive fuel is replaced with solar energy, an increased number of tubes is found to be more viable.

NOMENCLATURE

A	Collector area, m^2
b	Bond width , m
C_b	Bond conductance, W/mK
c_p	Specific heat capacity, J/kgK
D	Riser tube outside diameter, m
D_i	Riser tube inside diameter, m
F′	Collector efficiency factor
F	Fin efficiency
F_R	Heat removal factor
h_{fi}	Heat transfer coefficient inside absorber tube, W/m^2K
I	Solar radiation, W/m^2
k	Absorber thermal conductivity, W/mK
k_b	Bond thermal conductivity, W/mK
m	Mass flow rate, kg/s
N	Number of riser tubes
Q_u	Rate of useful energy collected, W
T_a	Ambient temperature, K
T_i	Collector inlet temperature, K
U_b	Bottom heat loss coefficient, W/m^2K
U_e	Edges heat loss coefficient, W/m^2K
U_o	Heat transfer coefficient from fluid to ambient air, W/m^2K
U_L	Overall heat loss coefficient, W/m^2K
U_t	Top heat loss coefficient, W/m^2K
W	Distance between riser tubes, m

Greek

γ	Average bond thickness, m
δ	Absorber (fin) thickness, m
ΔT	Temperature difference [$=T_i-T_a$], K
$\tau\alpha$	Transmittance-absorptance produce

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