

Optimization of a Thermodiode Panel (TDP) Sizes by Employing Genetic Algorithm (GA)

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Abstract

A Generic Algorithm (GA) code is developed to optimize the sizes of the TDP for Toronto weather conditions to gain maximum solar thermal energy on an annual basis.

GA codes are written in Matlab for five main sizes of the TDP components: front, middle and back aluminum plate thicknesses, thermosyphon outer diameter and its thickness. Thermosyphon is constructed from copper tube, which passes through the adiabatic layer of the TDP to transfer heat from outside (evaporator) to inside (condenser).

The plate thicknesses are found to be 3mm, 3mm, and 1mm and thermosyphon diameter and thickness of 25mm and 10mm, respectively. The TDP optimal dimensions are then checked for mechanical stability using SolidWorks. The resulting maximum strain is found less than 0.01% due to combined thermal and mechanical stress, which makes the reliable structure.

1 Introduction

Thermodiode panel (TDP)

A two-phase closed thermosyphon is a simple but effective heat transfer device (Chen, et al., 2002); (Dunn & Reay, 1994); (Esen & Esen, 2005); (Tundee, et al., 2010); (Imura, et al., 2005). It is an evacuated closed pipe, constructed from copper tube, with a liquid pool at the bottom (Figure 1). It is best described by its three sections: condenser with length of L_c , adiabatic with length of L_a , and evaporator with length of L_e . Heat is input through the evaporator section where the liquid pool exists, turning the saturated working fluid into a vapour. The vapour rises and passes through the adiabatic section to the condenser section, where the vapour condenses and gives up its latent heat of evaporation (h_{lv}). The condensate falls back to the evaporator section by gravity. It is interesting that the thermosyphon has no macro scale moving parts and is considered fully passive (Singh, et al., 2011).

“Thermal diode” or “thermo-diode” refers to a thermal system component that allows heat transfer only in the desired direction, but blocks the flow of heat in the opposite direction. The terms “thermo-diode” and “thermal diode” were used interchangeably in the past. However, in recent years a thermal diode has been commonly used for thermionic or thermoelectric devices that generate electricity directly from heat (Chun, et al., 2009). A two-phase thermosyphon is core of a thermo-diode panel (TDP), Figure 2, enclosure that transfers heat against gravity (forward direction) and the condensate moves back by the gravity (backward). Recently, utilization of the TD has received much interest in research to reduce energy demand and to enhance the performance of building envelopes (Varga, et al., 2002). TDP has potential applications for energy efficiency of buildings to transfer thermal energy from incident solar radiation and conduct it through the panel to the building structure during the heating season.

It also acts as an insulating material and reduces heat loss when the building structure is at a higher temperature than the external surface.

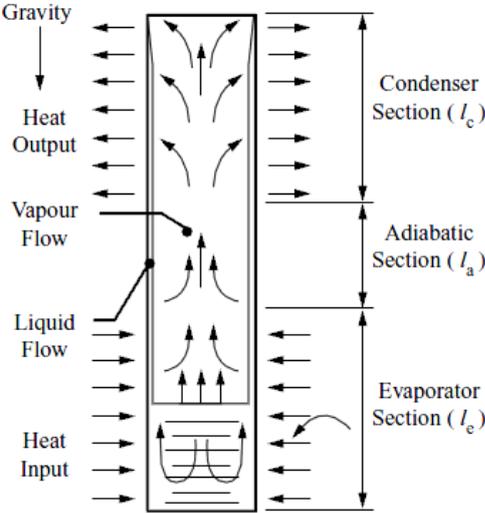


Figure 1: Conventional thermosyphon structure (Joudi & Witwit, 2000)

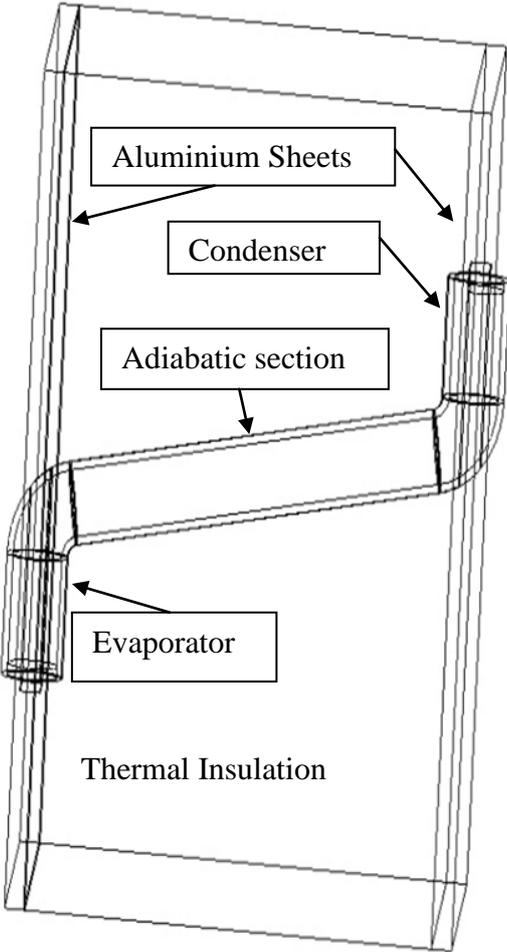


Figure 2: Sketch of the TDP components, evaporator is subjected to solar radiation and condenser is inside the home/zone

Genetic Algorithm (GA)

Genetic Algorithms (GAs) are a series of computational types inspired by evolution. GAs were mostly developed in the 1970s as an optimization toolbox, though some work had already been done in the field of evolutionary computation. These algorithms are often viewed as function optimizers. In 1967, Bagley introduced the words “genetic algorithm” and published the first application of GAs. However, Holland (Holland, 1992) and De Jong were the first who started using the GA in their works. In the 1980s, Grefenstette, Baker and Goldberg contributed to significant advancements in GAs. A more complete history of GAs and other evolutive computation methods is given in (Gosselin, et al., 2009).

In canonical GA, fitness is defined by f_i/\bar{f} where former/numerator is the evaluation associated with string i and latter/denominator is the average evaluation of all the strings in the population. Most of the time, the initial population is generated randomly. A fitness value is evaluated and assigned after creating an initial population. GA starts with the current population and creates an intermediate population from the current one. Later, recombination and mutation are applied to the intermediate population to create the next population. This is the execution of one generation process (Whitley & Starkweather, 1990).

However, the interest in and the utilization of GAs in the field of heat transfer is more recent. This is probably due to the fact that for most numerical problems, in which the heat transfer community is interested in, computational times are typically long. In the GA optimization procedure, several simulations typically need to be performed. When, for example, CFD analysis is part of the simulation, the overall computational time required for the GA to run could be prohibitive. Nevertheless, GAs began to be used in heat transfer approximately in the mid-1990s, timidly at first, but more and more regularly nowadays (Gosselin, et al., 2009). Due to availability of high performance computers, recently much more complicated mathematical heat transfer problems can be solved easily. GAs have generated a lot of interest in the field of heat transfer, in particular, in the last couple of years. Even though they have some limitations, GAs appear as a promising and accessible alternative for the optimization and design of thermal systems (Gosselin, et al., 2009).

Genetic algorithms are implemented as a computer simulation in which a population of abstract representations (called chromosomes or the genotype or the genome) of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem evolves toward better solutions (performance). Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Figure 3 summarizes a general GA procedure. The evaluation of the objective value or performance is the most time-consuming step of the GA procedure because it involves several simulations. This is why many researchers have used an approximation of the design space associated with their problem rather than performing simulations to evaluate precisely the performance of each individual. As utilization of TDP in buildings is a new idea, optimization of its sizes (reducing the price and increasing solar gain) could help increase its application in new buildings.

2 Methodology

Generic algorithm (GA) module of Matlab is used to optimize the main five sizes of the TDP. These sizes are selected based on the price contribution into the final product (TDP). A TDP is composed of thermosyphon (sealed copper tube), aluminum sheets and insulating materials

(thermal insulator). The TDP under investigation is integrated with a layer of phase change material (PCM); therefore, there are three aluminum plates separating layers. These are five main sizes under optimization: front (t_1), middle (t_3) and back aluminum plate thicknesses (t_5), copper outer diameter (OD) and thickness (t_c), (see Figure 4).

The objective of the GA code is to maximize the solar thermal energy gain (Q_{in}) for Toronto weather conditions on an annual basis:

$$Objective\ function = \sum_0^{8760} \begin{cases} -Q_{in} & \text{if } 2881 < time < 6552 \\ Q_{in} & \text{if time is other values} \end{cases} \quad (1)$$

Objective function is calculated in favor of comfort, i.e., it adds Q_{in} in forward (positive values) in winter with Q_{in} in reverse (negative values) in summer. Summer is considered from hour 2881 to 6552; the other time of the year is considered as winter (8760 is the number of hours in one year). Thermal resistance of the panel is $\sum R$:

$$\sum R = R_{ts} + R_t \quad (2)$$

where R_t is all thermal resistant inside the panel except thermosyphon, R_{ts} is the thermosyphon thermal resistant. The value of R_{ts} changes based on the direction of heat transfer and the outside surface temperature of the panel (T). Figure 5 shows the algorithm of calculating Q_{in} , or objective function value. More details about heat transfer equations are given in another paper (Poulad & Fung, 2012).

Surface temperature (T) is calculated from the following equation, which is derived based on first law of thermodynamics on a control volume:

$$\alpha q_{solar} = \frac{T - T_{in}}{\sum R} + [\bar{h}_o(T - T_{air}) + \varepsilon\sigma(T^4 - T_{\infty}^4)] \quad (3)$$

where ε is solar emissivity of the surface under investigation, σ is Stephen-Boltzmann constant ($5.67 \times 10^{-8} \text{ W/m}^2\text{K}^4$), T_{∞} is sky temperature (K), T_{air} is air/ambient temperature (K), T is the surface temperature (K), \bar{h}_o is average convective heat transfer coefficient ($\text{W/m}^2\text{K}$), α is absorptivity of the surface, T_{in} is the inside temperature of the panel (this is assumed 20°C) and A is the exposed surface to radiation (m^2). At each hour Q_{in} is calculated by:

$$Q_{in} = \frac{T - T_{in}}{\sum R} \quad (4)$$

The input array for each of the three aluminum thickness is [1, 1.5, 2, 2.5, 3] and for copper pipe outer diameter (OD) and thickness are [25:50] and [1:10], respectively. All units are in millimeter. Population size, (pop_size), generation size, mutate rate and cross rate are given by operator interactively. The range of the first two values is a natural number between 5 and 100 and the range of the two latter is real number between 0 and 1. Figure 6 demonstrate the flow chart of the GA. The thermosyphon is designed to boil water at 40°C ; therefore, when the surface temperature is higher than 40°C (forward in Figure 5), heat transfers in forward direction. In this direction thermal resistance of the thermosyphon (R_{ts}) is:

$$R_{ts} = \frac{\ln \frac{r_o}{r_i}}{2\pi k_{Cu}} \left(\frac{1}{L_c} + \frac{1}{L_e} \right) + \frac{\pi r_o^2 T_v F_v \left(\frac{L_e}{6} + L_a + \frac{L_c}{6} \right)}{\rho_v h_{lv}} \quad (5)$$

$$F_v = \frac{8\mu_v}{\rho_v h_{lv} r_{h,v}^2 A_v} \quad (6)$$

where F_v is frictional coefficient for circular vapour-flow passage (Chi, 1976), subscript v refers to vapour phase, $r_{h,v}$ is hydraulic radius of vapour ($\approx r_i$), r_i , r_o , and A_v are the internal and external radius, and inner cross section area of the thermosyphon, respectively, L_e , L_a , L_c are evaporator, adiabatic and condenser length, in turn, and k_{Cu} is thermal conductivity of copper. When the surface temperature is less than 40°C (backward in Figure 5), the thermal resistance of thermosyphon is calculated as the resistance of the copper pipe as follows:

$$R_{ts} = \frac{L}{k_{Cu}\pi(r_o^2 - r_i^2)} \quad (7)$$

where L is the length of thermosyphon structure (i.e., $L_e + L_a + L_c$).

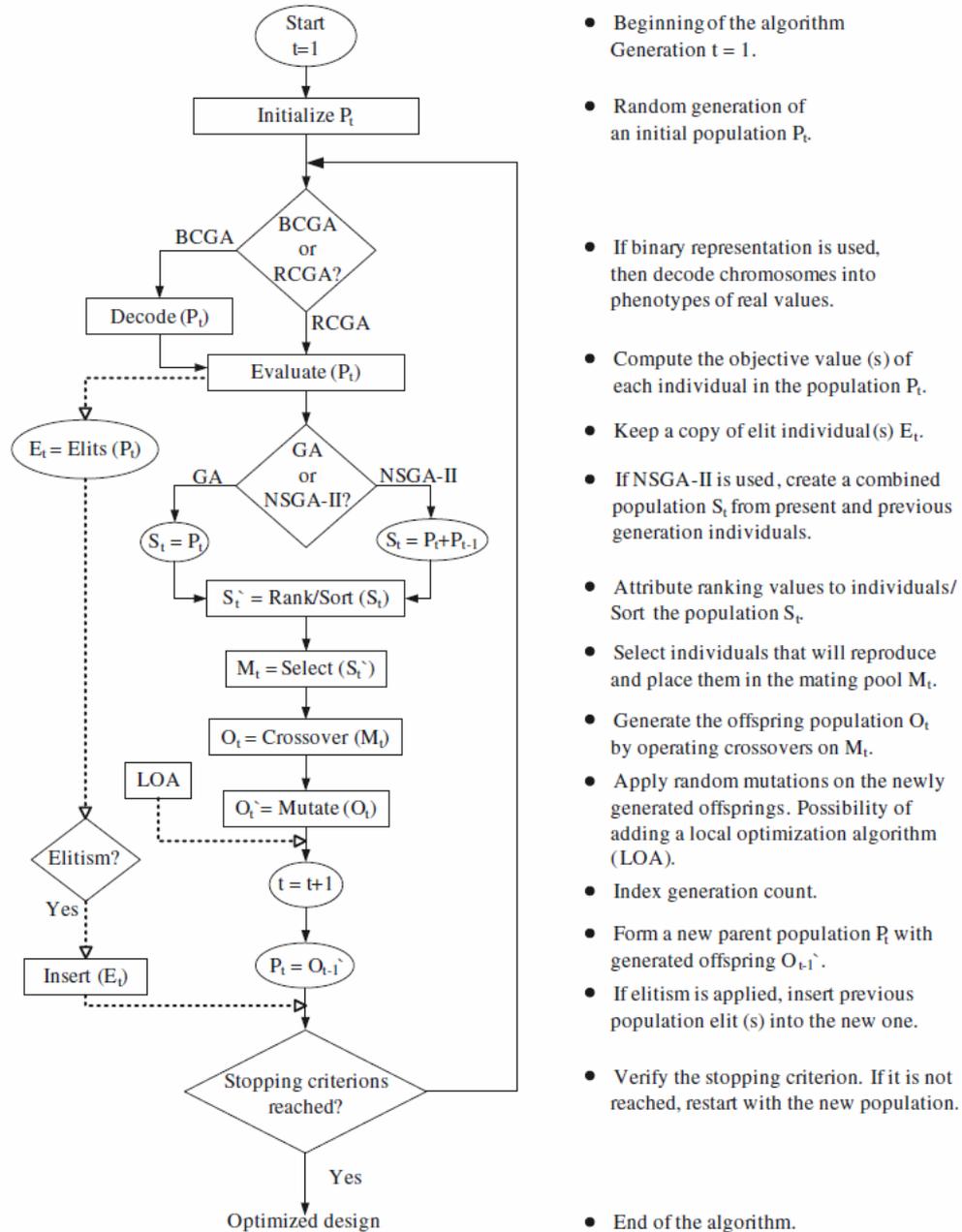


Figure 3: The main steps of a typical GA (Gosselin, et al., 2009)

Finally, the displacement or strain due to the thermal stress is analysed for the design parameters suggested by GA. In this analysis, the heat transfer is simulated with SolidWorks 2011 solver. As there is no external stress on TDP, the thermal loads on the evaporator surface are simulated as follows: Convection coefficient, 2W/K.m^2 ; bulk ambient temperature, 20°C ; ambient/sky temperature, 20°C ; emissivity of the radiated surface, 0.97; view factor, 1; constant heat flux, 1000W/m^2 ; and indoor temperature, 20°C .

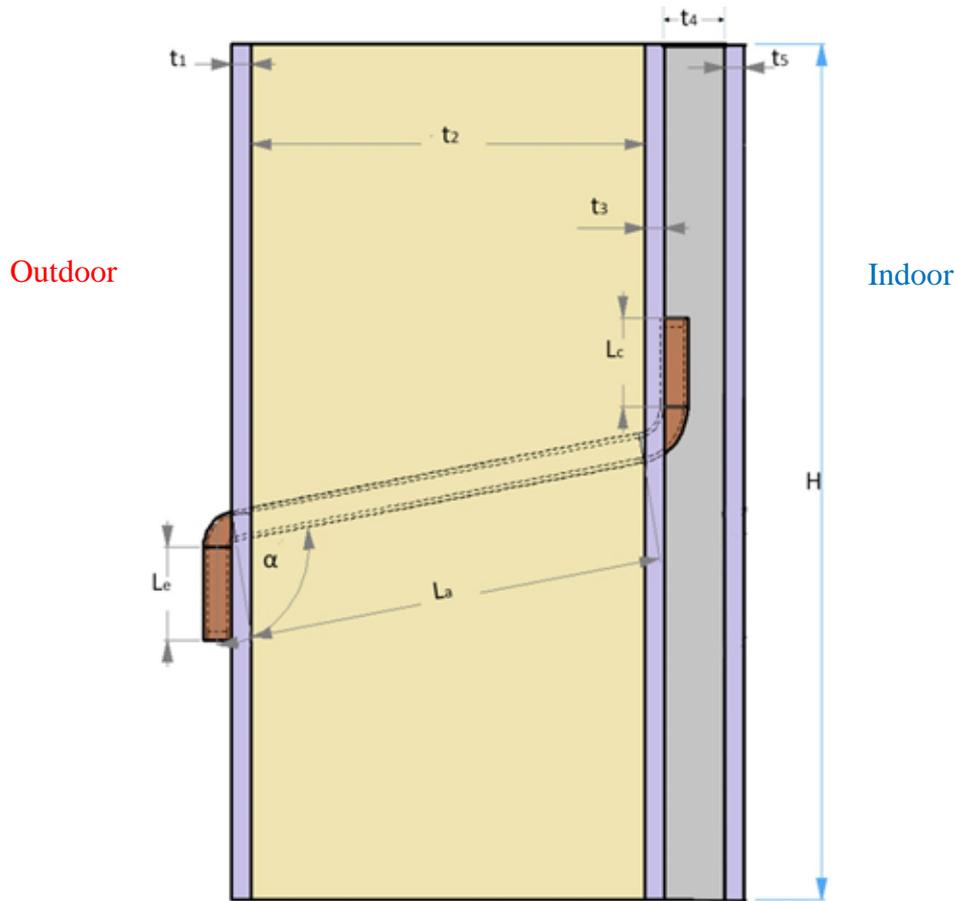


Figure 4: TDP cross section, t_2 and t_4 are the thickness of thermal insulator and PCM, respectively. Three aluminum plates are shown with thicknesses of t_1 , t_3 and t_5

3 Results

GA codes are written in Matlab 2013. A 64-bit operating system with 16 GB RAM and Intel® Core™ i7-2600 CPU processor at 3.40GHz desktop computer is employed for this work. It has four processor cores.

The input matrices are given as follows: the three aluminum thickness are called v_1 to v_3 and $v_1 = v_2 = v_3 = [1, 1.5, 2, 2.5, 3]$, and copper pipe outer diameter (OD) is $v_4 = [25:50]$, 25 to 50 with one increment, and thickness of $v_5 = [1:10]$. Population and generation sizes, hybrid and mutate rates are given interactively to the GA.

Table 1 provides a summary of the results. Population size multiplied by the Generation size is the number of cases that GA evaluates for optimization each time (first column in the Table 1). The time for each optimization varies from 0.34 hour (6 cases) to 37.84 hours (1000 cases). The last column of the table represents the GA suggestions (optimal values).

Figure 7 shows average fitness versus generation size for two different conditions. The information related to each simulation is added below the plots.

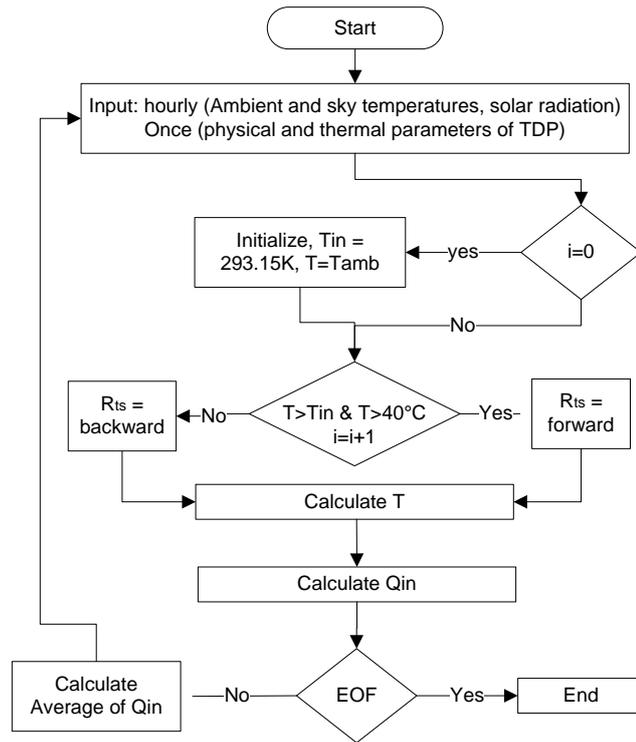


Figure 5: Flow chart for calculating objective function, $\sum_{i=0}^{8760} Q_{in}^i$

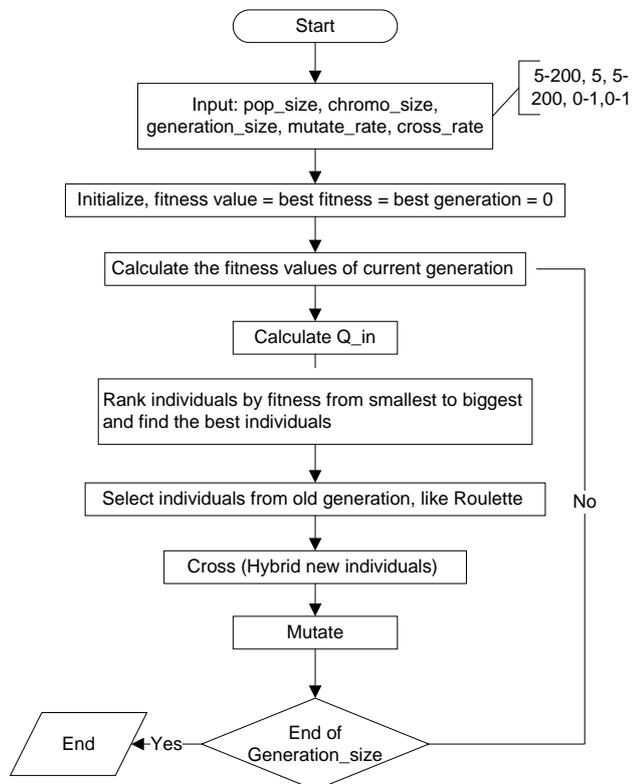
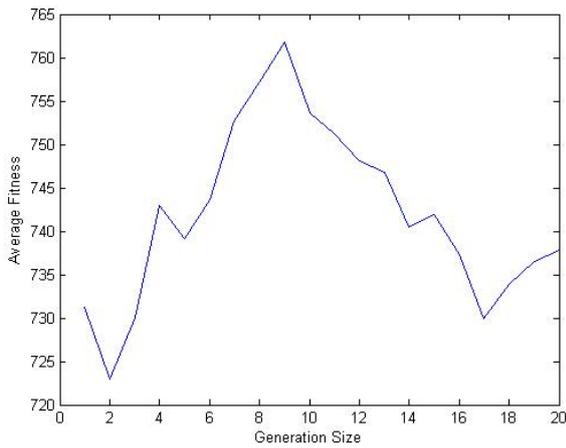


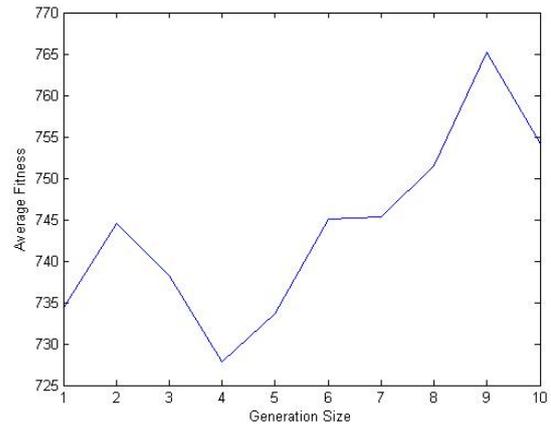
Figure 6: Flow chart for Genetic Algorithm process

Table 1: GA suggestions based on different interactive inputs

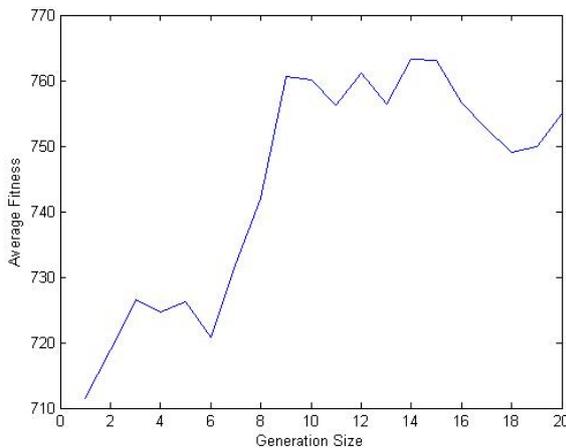
# of Cases	Pop. size	Gen. size	Hybrid rate	Mutate rate	Obj. Fun. Value (J)	Comp. Time (h)	GA Suggestion, [v1,v2,v3,v4,v5]
10	5	2	0.2	0.3	760.35	2.12	[3, 2, 1, 28, 3]
6	3	2	0.6	0.9	758.68	0.34	[2.5, 2, 3, 26, 4]
12	4	3	0.8	0.9	793.55	0.42	[3, 2.5, 1.5, 28, 3]
1000	100	10	0.6	0.2	820.58	35.95	[3, 3, 1.5, 25, 7]
1000	50	20	0.8	0.7	823.52	37.84	[3, 3, 2, 25, 10]
100	20	5	0.8	0.8	791.09	3.84	[2.5, 1.5, 1, 25, 7]
100	10	10	0.9	1	805.38	3.71	[1.5, 3, 2, 27, 6]
400	50	8	0.9	0.7	820.04	13.76	[3, 3, 1, 26, 10]
800	40	20	0.9	0.7	818.34	30.19	[3, 3, 1, 26, 8]
220	22	10	0.8	0.6	818.41	8.33	[3, 3, 2, 26, 8]



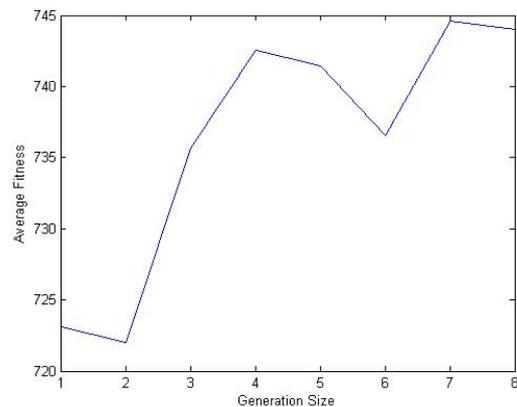
A) Pop_size = 50; Hybrid & Mutate rates = 0.8 & 0.7



B) Pop_size = 22; Hybrid & Mutate rates = 0.8 & 0.6



C) Pop_size = 40; Hybrid & Mutate rates = 0.9 & 0.7



D) Pop_size = 50; Hybrid & Mutate rates = 0.9 & 0.7

Figure 7: Generation size versus average fitness in four different conditions

Figure 8 represents the different values selected by GA to evaluate the objective function. It represents 100 cases (20 populations multiplied by 5 generations). The randomly selected 20 populations are shown in Table 2. V1 to V5 are selected randomly from the input matrices. During GA, new generation is produced by mutation and cross over process (five times in this case); therefore, altogether hundred scenarios are evaluated.

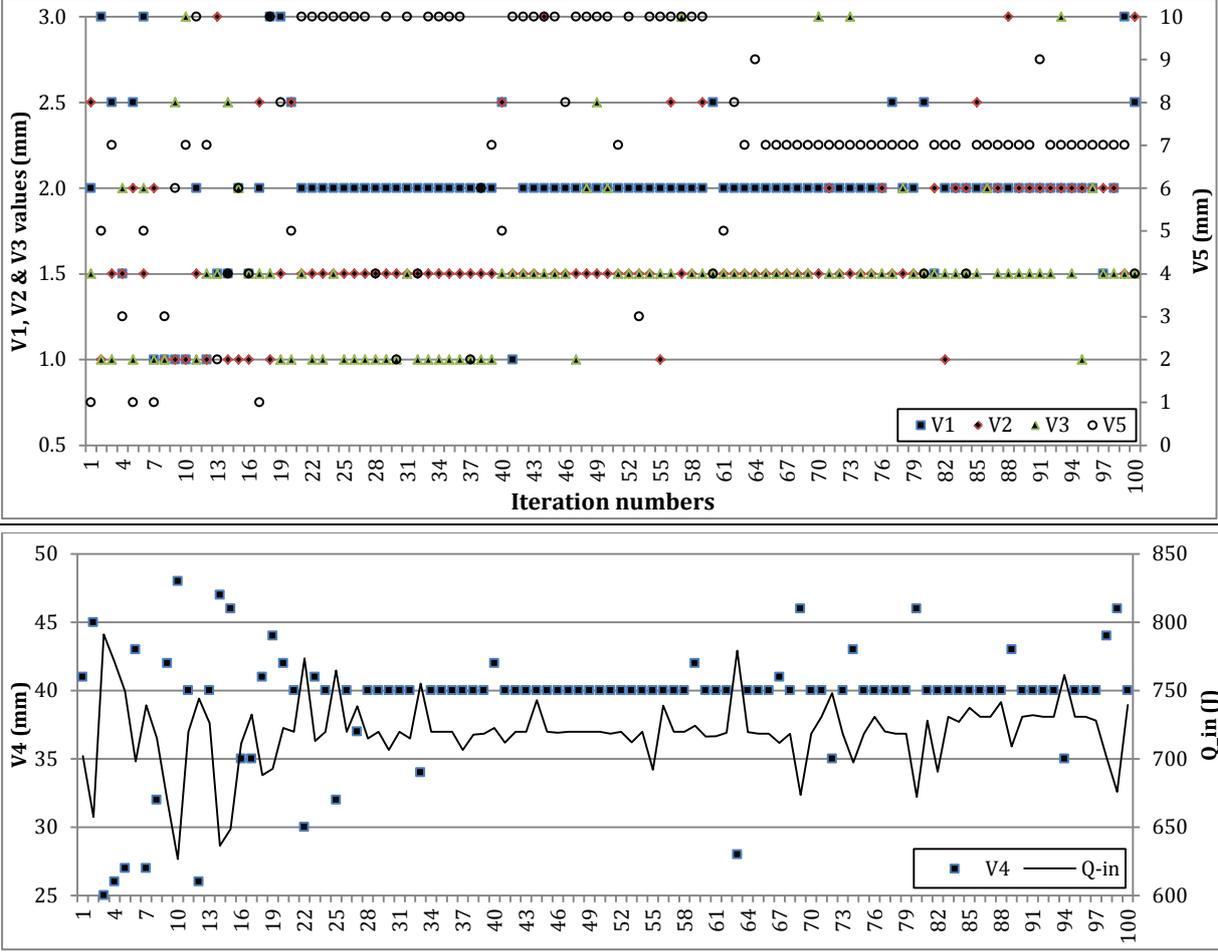
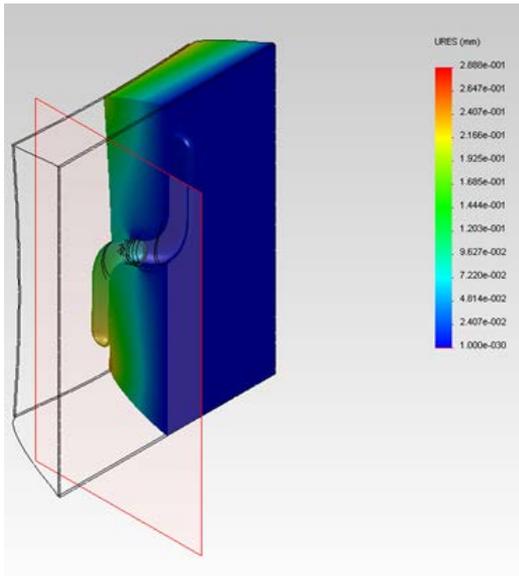


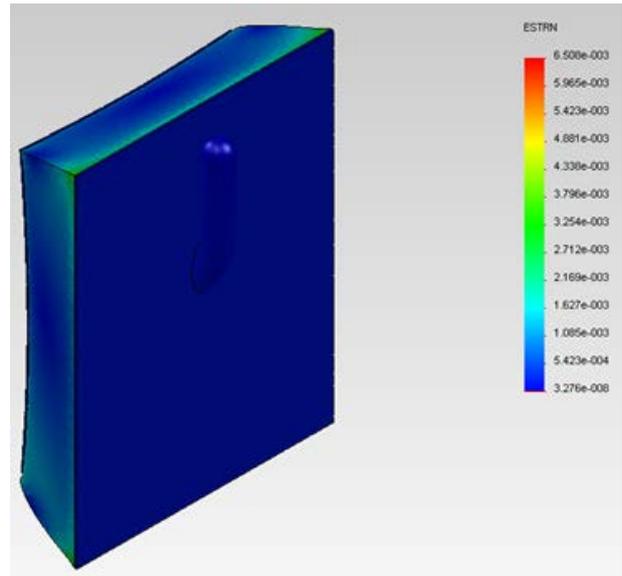
Figure 8: graphical results for the number of cases of 100 (20 populations times 5 generations), V5 (top) and Q_in (bottom) are shown on the secondary axes

The results of thermal analysis in SolidWorks are transferred for displacement analysis. The results show that the displacement of the suggested design is in safe condition. The maximum resultant displacement and strain are found to be 0.29mm and 0.007, respectively (Figure 9). The problem domain is subdivided into 267,411 nodes and 188,025 tetrahedron (triangular base) elements. Static analysis and the FFEPlus¹ solver with a mesh size of 3 to 8mm (with no distortion and high quality) is employed.

¹ The FFEPlus solver is an iterative solver. After having the CAD model set up with the appropriate boundary conditions, the FFEPlus solver makes an educated guess about the deformation, [U], of the model. Then it evaluates the matrix equations to see how good the guess was, and adjusts the deformation accordingly, depending upon the error in the calculation. This process repeats until the calculation balances.



A) Max. resultant displacement is 0.2889mm at
Node: 249049



B) Max. equivalent strain is 0.00650757 at
Element: 22470

Figure 9: displacement (A) and strain (B) on TDP at severe condition

Table 2: Randomly selected population, when Pop_size = 20

#	V1	V2	V3	V4	V5
1	1.5	2	1.5	40	7
2	2	1	1.5	30	2
3	1	2	1.5	34	4
4	2	2	1.5	35	1
5	2	2.5	1.5	25	10
6	2	2	2	40	7
7	2	2	1.5	28	3
8	2	3	1.5	40	7
9	2	2	1.5	43	7
10	2	2	1.5	40	7
11	2	2	1.5	27	9
12	2	2	1.5	40	8
13	1	2	3	45	7
14	2	2	1.5	35	7
15	1.5	2	1	41	5
16	2	2	2	36	6
17	1.5	2	1.5	40	7
18	2	2	1.5	50	1
19	3	1.5	1.5	46	7
20	2.5	3	1.5	48	4

4 Discussions

There are 31,250 ($25 \times 10 \times 5 \times 5 \times 5$) different ways that one can make a TDP with the given values on Table 1. Only one of the above combinations (desired one) maximizes the objective function (Q_{in}). Using genetic algorithm technique, it is possible to reach to the best (optimal) solution fast. As Figure 9 stipulates, the maximum value for Q_{in} increases by increasing the number of cases (best fits are also shown in the plots). Maximum values of Q_{in} are best fit with a degree three polynomial and time is linearly dependant on the number of the cases. Plot of Q_{in} versus the number of case could also fit a power series (ax^b). For the range of 0 to 1000 for the number of cases, the polynomial fit produces higher R^2 .

Analysis of graphs in Figure 7 shows that generation size of more than 10 does not increase the fitness values for this specific study. Checking the data generated by GA shows that some individuals are repeating themselves when the generation size is higher than 10. By increasing the generation size the chance of repetition increases. In addition, comparison of case A with C reveals that fitness reaches its maximum value faster when the population size is higher.

The difference between maximum and minimum values in different cases (Figure 10) is less than 4 percent. This means if results are sought with less than 5 percent, any of the above cases could bring optimized parameters. The implication is that GA can provide optimized parameters no matter what the values of population and generation sizes, and mutation and hybrid rates are. By increasing the population and generation sizes, computation time and objective function value increase, which produce better individuals (design parameters). Rate of increase of Q_{in} is high at first (up to number of cases equals to 200) and hardly increases after 220. That means, GA approaches to the best individuals very fast. After this point, increasing the number of cases is not very effective.

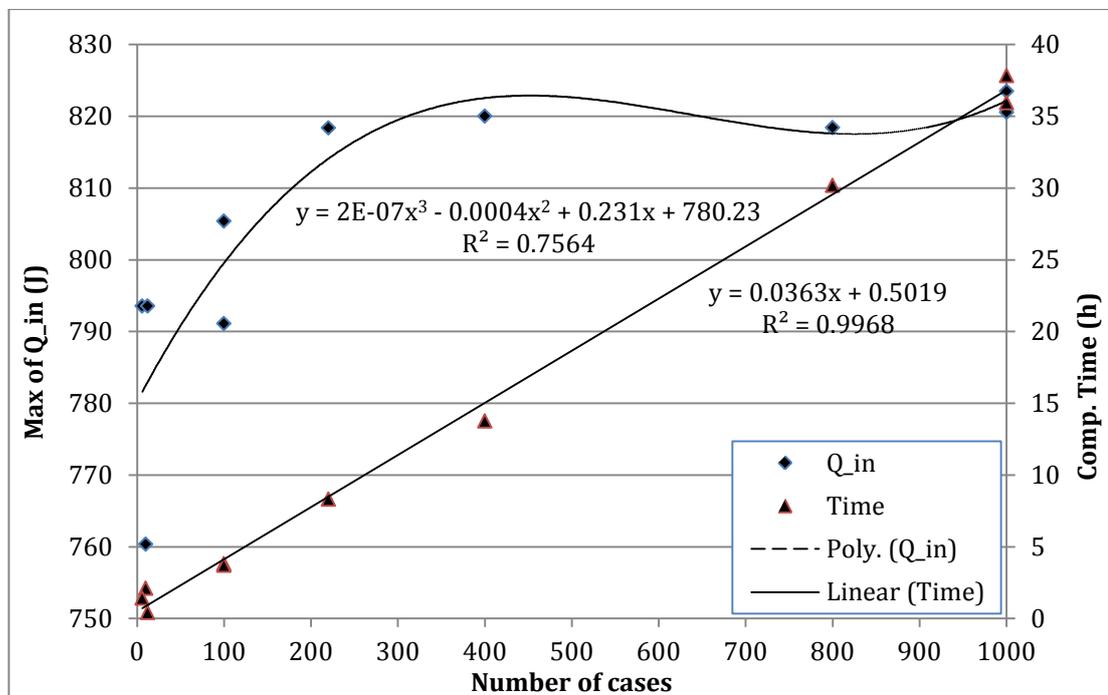


Figure 10: graphical results for different cases

5 Conclusions

A Generic Algorithm code is developed to optimize the dimensions of the TDP for Toronto weather conditions to gain maximum solar thermal energy on an annual basis. GA codes are written in Matlab for optimizing the physical size of the five main TDP components: front, middle and back aluminum plate thicknesses, thermosyphon outer diameter and its thickness. Thermosyphon is constructed from copper tube, which passes through the adiabatic layer of the TDP to transfer heat from outside (evaporator) to inside (condenser). The plate thicknesses of 3mm, 3mm, and 1mm and thermosyphon diameter and thickness of 25mm and 10mm, respectively, provide the maximum fitness value; therefore, they are the best individuals (optimum values). The determined TDP optimal dimensions are then checked for mechanical stability using SolidWorks 2012. The resulting maximum strain is found less than 0.01% due to combined thermal and mechanical stress, which makes the reliable structure.

6 Acknowledgements

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