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THERMAL DESIGN OF FIN-AND-TUBE HEAT EXCHANGERS USING PARTICLE SWARM OPTIMIZATION

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Abstract. *Fin-and-tube heat exchangers (FTHEs) are widely used in power engineering and chemical engineering applications mainly because of their high compactness. The traditional design approach for Fin-and-tube heat exchangers involves rating a large number of different exchanger geometries to identify those that satisfy a given heat duty and a set of geometric and operational constraints. However, this approach is time-consuming and does not assure an optimal solution. This paper applies a particle swarm optimization (PSO) technique for design optimization of FTHEs by considering both the total annual cost and the total weight as the objective function. The design parameters considered are the geometric properties of the heat exchanger in a total of 7 variables. In order to evaluate the PSO algorithm, five PSO methods were used varying the size of the population (particles) for comparison purposes and the results were also compared with the genetic algorithm (GA).*

Keywords: *Optimization, Fin-and-tube heat exchangers (FTHEs), Particle swarm optimization (PSO)*

1. INTRODUCTION

Fin-and-tube heat exchangers (FTHEs) are used mainly due to its compactness, especially in power engineering and chemical engineering applications. The surface area of contact with the cooling fluid is important due to its low heat transfer coefficient, as the most commonly used fluid in refrigeration, power generation and air conditioning systems is air. The fins increase enormously the heat transfer performance of the tubes, and their morphology is very important to guarantee an optimal increase.

The FTHEs are employed in many areas of engineering. They are applied as compressor inter-coolers, air-coolers, fan coils as well as HVAC&R (heating, ventilating, air-conditioning and refrigeration). Because the relatively large thermal resistance is encountered on the gas-side (generally air-side), fins are employed on the gas-side to enlarge the heat exchanger surface area and increase the disturbance of the flow. (Xie at al., 2009).

Many factors are considered in the design of fin-and-tube heat exchangers, such as the area cost, the power cost, the fabrication limitations in size and shape, the geometrical properties of the fins and tubes. Because of that, it is often a long iterative process of trial and error to obtain a reasonable design that meets all the required constraints (Patel and Rao, 2010). Depending on the application, the factor one may want to maximize or minimize may be different from other cases. Particle Swarm Optimization (PSO) is one of the optimizations algorithms that can be used to provide the design of FTHE. It is has been used in several thermal problems such as the prediction of heat transfer coefficient (Malekan and Khosravi, 2018), optimization of thermal generation systems (Zhao et al., 2018, Nogueira et al., 2018 and Mabrouk et al., 2018) and also to increase the heat transfer of thermal systems (Payan and Azimifar, 2016).

In this paper the PSO algorithm was applied in a case study to optimize two objective functions separately, the total annual cost and the total weight of a Fin-and-tube heat exchanger (Xie et al., 2008). In order to evaluate the PSO algorithm, five PSO methods were used varying the size of the population (particles) to verify the sensibility of the results regarding the number of particles. The objective functions were also optimized with Genetic Algorithm (GA) in order to compare the results with PSO algorithm and verify its effectiveness, since the GA algorithm it is a very known algorithm and it also has been used for the optimization of heat exchangers (Xie et al., 2008 and Sunden et al., 2007).

2. DESCRIPTION OF THE GENECTIC ALGORITHM METHOD

Genetic algorithms (GA) are optimization methods that are based on the process of natural selection. The algorithm starts creating a random population of designs (individuals) that is improved at each generation by exchanging genetic information between designs in the current population through the crossover operation. The purpose of this operation is to produce improved designs that will compose the next generation (Goldberg, 1989). At each generation in the GA algorithm, three operators are applied to the entire population of designs, namely: selection, crossover, and mutation.

Each potential solution or design must be represented as a collection of finite parameters, also called genes, so each individual is represented by have a unique sequence of these parameters that define it (the chromosome). The genes are expressed as binary strings though they can be represented as real numbers. The length of the binary string determines how precisely the value is represented (Colaço et al., 2006).

The initial population creates the designs (individuals) randomly generating 0's and 1's for each gene. After combining the genes together, the chromosome strings are formed. Having the initial population, the objective function is evaluated for each design. Then for each design is assigned a fitness value, which corresponds to the value of the objective function for that design. A higher fitness is assigned to designs with lower values of the object function in case of minimization.

Using the fitness value of each individual, the population members are selected for reproduction. The selection operator is applied to each member and will determinate the pairs of individuals from the population who will mate and produce offspring. In this case, random pairs are selected from the population and the individual with the higher fitness of each pair is allowed to mate. Then the crossover operator is applied to produce new designs by combining the genes from the parent designs in a stochastic manner. For the uniform crossover scheme, it is possible to obtain any combination of the two parent's chromosomes. Each bit in each gene in the chromosome is assigned a probability that crossover will occur. By the end of this process, two offspring will be generated and a new population is formed (Colaço et al., 2006).

Afterwards the mutation operator is applied in each bit in each gene in the design, subjecting it to a chance to change from 0 to 1, or vice versa. The algorithm converges to the best suited individual between those created, which represents the best answer it has found for the given problem. More details of Genetic Algorithm can be found in Goldberg (1989), Michalewicz (1999), Michalewicz and Fogel (2000) and Colaço et al. (2006).

3. DESCRIPTION OF THE PARTICLE SARM OPTIMIZATION METHOD

The particle swarm optimization was proposed by Kennedy and Eberhart proposed in 1995 inspired by the concept of swarm intelligence, often seen in animal groups, such as flocks and shoals and its social behavior. It's possible to understand the algorithm imaging a swarm of birds flying over a place must find a point to land. The definition of which point the whole swarm should land is a complex problem, since it depends on several issues, that is, maximizing the availability of food and minimizing the risk of existence of predators. In this case, the birds synchronically move for a period until the best place to land is defined and all the flock lands at once (Kennedy and Eberhart, 1995).

The PSO is appropriate to optimize nonlinear continuous functions and it is a type of Heuristic methods. In general, Heuristic methods, in contrast to deterministic methods, do not use the objective function gradient as a downward direction. Its goal is to mimic nature in order to find the minimum or maximum of the objective function by selecting, in an elegant and organized manner, the points where such a function will be calculated (Colaço et al., 2006).

The version proposed by Kennedy and Eberhart in 1995 is called the classical version or inertial version. Other versions have been proposed as variations of the classical formulation. The linear-decreasing inertia weight was proposed by Shi and Eberhart (1999), the constriction factor weight by Eberhart and Shi (2000), the dynamic inertia and maximum velocity reduction, also by Eberhart and Shi (2000), besides hybrid models as those proposed by Coelho and Mariani (2006) or even quantum inspired approach optimization techniques that can be applied to PSO as proposed by Han and Kim (2002).

The overall formulation of classical version of the algorithm is presented in Eq. (1) and Eq (2).

$$x_i^{k+1} = x_i^k + V_i^{k+1} \tag{1}$$

$$V_i^{k+1} = wV_i^k + c_1 r_{1i}\left(p_{best,i} - x_i^k\right) + c_1 r_{2i}(g_{best} - x_i^k) \tag{2}$$

In the first term of Eq (2), the parameter w is the inertia weight constant, and for the classical PSO version, it is a positive constant value. This parameter balances the global search (exploration) and local search (exploitation). It $w = 1$, the particle's motion is fully influenced by its previous motion, so the particle may keep going in the same direction. If $0 < w < 1$, such influence is reduced and that particle rather goes to other regions in the search domain.

The second term of Eq. (2), is calculated by means of the difference between the particle's own best position ($p_{best,i}$) and its current position x_i^k. So this term gives an idea of how far the particle is of its best position an then attracting the particle to its best own position. The parameter c_1 weighs the importance of particle's own previous experiences. The term r_1 is a random value parameter on the range $0 < r_{1i} < 1$ and it is responsible to avoid premature convergences, increasing the most likely global optima (Kennedy and Eberhart, 1995).

The third term of Eq. (2) is defined as the social learning. Its responsible for letting all particles in the swarm to share the information of the best point achieved regardless of which particle had found it, so the best position of the whole swarm until that iteration (g_{best}). The difference term ($g_{best} - x_i^k$) acts as an attraction for the particles to the best point until found in the k iteration. The parameter c_2 weighs the importance of the global learning of the swarm and the term r_2, as the r_1, is a random value parameter on the range $0 < r_{1i} < 1$ ant it is responsible to avoid premature convergences

4. FIN-AND-TUBE DESIGN DESCRIPTION

In the present study the FTHE considered is an intercooler in which hot air flows normal to a finned tube bundle, while cold water flows inside the smooth tubes, as shown in Fig. 1. The design parameters are the shape length, *L*, shape width, *W*, shape height, *H*, outside diameter of tube, D_o, fin collar outside diameter, D_c, tube thickness, δ_t, longitudinal tube pitch, P_l, transverse tube pitch, P_t, fin pitch, F_p, fin space, F_s, fin thickness, δ_f, and number of tube rows, *N*. For this paper, both the fin and tube thicknesses are assumed constant following the work of G. Xien et al. (2008).

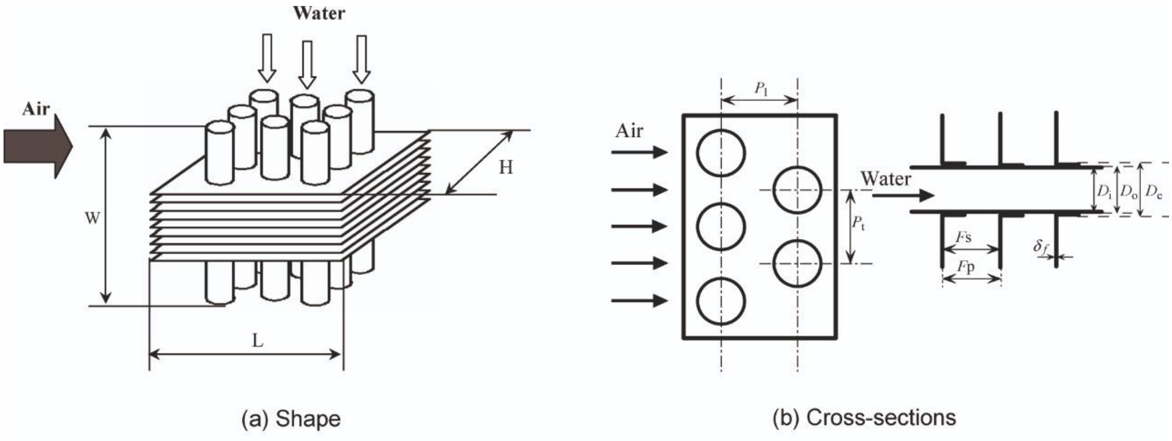

Figure 1. FTHE considered.

The material of the tubes is stainless steel with a thermal conductivity (k_c) of 15 W/(m· K), density (ρ_c) of 7820 kg/m^3. The fin material is aluminum with a thermal conductivity (k_h) of 170 W/(m· K) and density (ρ_h) of 2790 kg/m^3. Table 1. indicates the design specifications. The seven design parameters to be searched and used in the PSO method are as follows: *W*, *H*, *N*, D_o, P_t, P_l, and F_p. The other variables either can be obtained by combining those parameters or are constant values themselves.

Table 1. Design specifications

	Variables	Unit	Value
Air side	Flow rate	kg/s	58.2
	Inlet temperature	°C	104
	Outlet temperature	°C	21
	Inlet pressure	kPa	174.5
	Allowable pressure drop	Pa	5,200
Water side	Flow rate	kg/s	39.2
	Inlet temperature	°C	20
	Inlet pressure	°C	174.5
	Allowable pressure drop	kPa	5,200
	Heat Duty	kW	3115

The number of tubes (N_t) and the number of fins (N_f) can be obtained by Eq. (3) and Eq. (4), respectively.

$$N_t = \left(\frac{H}{P_t} - 1\right) N \quad (3)$$

$$N_f = \frac{W}{F_p} + 1 \quad (4)$$

Where H is the shape height, P_t is the transverse tube pitch, N is the number of rows and F_p is the fin pitch. For the Fin side, the minimum free flow area (A_{min}) can be calculated by Eq. (5).

$$A_{min} = (WH - NtD_0W - N_tP_t\delta_fN_f) \quad (5)$$

Where D_0 is the outside diameter tube and δ_f is the fin thickness. It is also necessary to obtain the total heat transfer surface area (A) of the heat exchanger that is calculate by the Eq. (6), Eq. (7) and Eq. (8).

$$A = A_p + A_f \quad (6)$$

$$A_p = \pi D_0WN_t(1 - \delta_fN_f) \quad (7)$$

$$A_f = 2N_f\left(LH - \frac{\pi}{4}D_0^2N_t\right) + 2\delta_fN_fWH \quad (8)$$

Where A_p and A_f are the primary surface area (tube) and secondary surface area (fin), respectively, and L is the shape length. Equation (9) indicates the Reynolds number of the fin side based on the fin collar outside diameter.

$$Re_{D_c} = \frac{G_aD_c}{\mu_a} \quad (9)$$

Where G_a is the air mass flux, D_c is the fin collar outside diameter and μ_a is the air viscosity. The hydraulic diameter D_h can be obtained by Eq. (10).

$$D_h = 4\left(\frac{A_{min}L}{A}\right) \quad (10)$$

The j-factors (Colburn factors) can be obtained by Eq. (11), (12), (13) and (14).

$$j = 0.086Re_{DC}^{j1}N^{j2}\left(\frac{F_P}{D_c}\right)^{j3}\left(\frac{F_P}{D_h}\right)^{j4}\left(\frac{F_P}{D_c}\right)^{-0.93} \quad (11)$$

$$j_1 = -0.361 - \frac{0.042N}{\ln(Re_{DC})} + 0.158ln\left(N\left(\frac{F_P}{D_c}\right)^{0.41}\right) \quad (12)$$

$$j_2 = -1.224 - \frac{0.076(P_l/D_h)^{1.42}}{\ln(Re_{DC})} \quad (13)$$

$$j_3 = -5.735 + 1.21\ln\left(\frac{Re_{Dc}}{N}\right) \quad (14)$$

Where P_l is the longitudinal tube pitch. Then the heat transfer coefficient on the air side (h_a) can be obtained by the Eq. (15).

$$h_a = j\frac{\rho_av_ac_{p,a}}{Pr_a^{2/3}} \quad (15)$$

Where ρ_a is the air density, v_a is the air velocity, $c_{p,a}$ is the air specific heat and $Pr_a$is the air Prandtl number. For the calculation of the pressure drop on the air side, it is necessary to calculate the friction factor (f) that can be obtained by Eq. (16), (17), (18) and (19).

$$f = 0.0267Re_{D_c}^{f1}\left(\frac{P_t}{P_l}\right)^{f2}\left(\frac{F_P}{D_c}\right)^{f3} \quad (16)$$

$$f_1 = -0.764 + 0.739\frac{P_t}{P_l} - 0.177\frac{F_p}{D_c} - \frac{0.00758}{N} \quad (17)$$

$$f_2 = -15.689 + \frac{64.021}{\ln(Re_{Dc})} \quad (18)$$

$$f_3 = 1.696 - \frac{15.695}{\ln(Re_{Dc})} \quad (19)$$

So the pressure drop of the air side (ΔP_h) can be obtained by the Eq. (20).

$$\Delta P_h = \frac{G_c^2}{2\rho_{a,i}}\left[\frac{A}{A_{frontal}}\frac{\rho_{a,m}}{\rho_{a,i}}f + (1+\sigma^2)\left(\frac{\rho_{a,i}}{\rho_{a,o}} - 1\right)\right] \quad (20)$$

Where G_c is water mass flux, $\rho_{a,i}$ is the inlet air density, $\rho_{a,o}$ is the outlet air density, $\rho_{a,m}$ is the average air density and σ is the cross-sectional area contraction ratio that can be calculated by Eq. (21).

$$\sigma = \frac{A_{min}}{WH} \quad (21)$$

For the Tube side, the Reynolds number can be calculated by Eq. (22).

$$Re_c = \frac{\rho_w v_w D_i}{\mu_w} \quad (22)$$

Where ρ_w is the water density, v_w is the water velocity, D_i is the inside diameter of the tube and μ_w is the water visocity. The friction factor for the tube can be obtained the Eq. (23).

$$f = (1.82\log_{10} Re - 1.64)^2 \quad (23)$$

The Nusselt Number of the water can be calculated by Eq. (24).

$$Nu = \frac{(f/8)(Re-100)Pr}{1+12.7\sqrt{f/8}(Pr^{2/3}-1)} \quad (24)$$

The heat transfer coefficient on the water side (h_w) can be obtained by the Eq.(25).

$$h_w = \frac{Nu.k_w}{D_i} \quad (25)$$

Where k_w is the water thermal conductivity. So the pressure drop of the water side (ΔP_c) can be obtained by the Eq. (26)

$$\Delta P_c = \frac{f.\rho_w.v_w^2}{2}\frac{L}{D_i} \quad (26)$$

For the calculation of the Required Heat Transfer Area (A_{req}), first it is necessary to calculate the logarithmic mean temperature difference (ΔTln) by the Eq. (27).

$$\Delta Tln = \frac{(T_{h,i}-T_{c,o})-(T_{h,o}-T_{c,i})}{\ln\left(\frac{(T_{h,i}-T_{c,o})}{(T_{h,o}-T_{c,i})}\right)} \quad (27)$$

Where $T_{h,i}$, $T_{h,o}$, $T_{c,i}$ and $T_{c,o}$ are the inlet hot side temperature, outlet hot side temperature, inlet cold side temperature and outlet cold side temperature, respectively. The Overall Heat Transfer Coefficient (U) can be calculated by the Eq. (28) (Mihailović et al., 2019).

$$U = \frac{1}{h_a}\frac{A_{tube}}{\eta A} + \frac{A_{tube}}{2\pi W k_h} ln\frac{D_c}{D_0} + \frac{A_{tube}}{2\pi W k_c} ln\frac{D_0}{D_i} + \frac{1}{h_w} + R_{fc} + R_{fh} \quad (28)$$

Where A_{tube} is the inside heat transfer area of the tube, R_{fc} is the water fouling factor, R_{fh} is the air fouling factor and η is the heat transfer surface efficiency that can be calculated by Eq. (29), (30), (31), (32), (33), (34) and (35) (Schmidt, T.E. 1949).

$$\eta = 1 - \frac{A_f}{A}(1-\eta_f) \quad (29)$$

$$\eta_f = \frac{\tanh\left(m\left(^{D_c}/_2\right)\phi\right)}{m\left(^{D_c}/_2\right)\phi} \quad (30)$$

$$m = \sqrt{\frac{2h}{k_f\delta_f}} \quad (31)$$

$$\phi = \left(\frac{R_{eq}}{\left(D_c/_2\right)} - 1\right)\left[1 + 0.35\ln\left(\frac{R_{eq}}{\left(D_c/_2\right)}\right)\right] \quad (32)$$

$$\frac{R_{eq}}{\left(D_c/_2\right)} = 1.27\frac{X_M}{\left(D_c/_2\right)}\left(\frac{X_L}{X_M} - 0.3\right)^{0.5} \quad (33)$$

$$X_L = \frac{\sqrt{(P_t/2)^2 + P_l^2}}{2} \quad (34)$$

$$X_M = \frac{P_t}{2} \quad (35)$$

So the required heat transfer area can be calculate by the Eq. (36).

$$A_{req} = \frac{Q}{UF\Delta Tln} \quad (36)$$

Where Q is the heat duty and F is the logarithmic mean temperature difference correction factor.
For this work, two objective functions are considered in the design process. The first one is the total weight (TW) and the second one is the total annual cost (TAC). Equation (37) indicates the total weight (TW) function.

$$TW = A_f\rho_f\delta_f + NN_t\rho_t W(D_o^2 - D_i^2) \quad (37)$$

Where ρ_f is the fin material density and ρ_t is the tube material density. The second one is the total annual cost (TAC) function that is indicated in Eq. (38), Eq. (39) and Eq. (40).

$$TAC(x_i) = C_{in} + C_{op} \quad (38)$$

$$C_{in} = C_A + A^n \quad (39)$$

$$C_{op} = \left\{k_{el}\tau\frac{\Delta PV_t}{\eta}\right\}_h + \left\{k_{el}\tau\frac{\Delta PV_t}{\eta}\right\}_c \quad (40)$$

Where C_{in} is the annual cost of investment (\$), C_{op} is the annual cost of operation (\$), C_A is price per unit area (\$/m^2), A is the heat transfer area (m^2), n is exponent of nonlinear increase with area increase, k_{el} is the price of electricity (\$/MWh), τ is the hours of operation per year, ΔP is the pressure drop, V_t is the volumetric flow rate (m^3/s) and η is the pump efficiency. The subscript h reffers to the hot side and the c reffers to the cold side.

5. METHODOLOGY FOR OPTIMIZATION

Seven design parameters are selected for optimization, as these parameters are sufficient for the design of a FTHE. They are varied within accepted ranges with their respective resolutions given the fabrication constraints. Table 2. indicates the search range of each variable (G. Xie et al., 2008).

Table 2. Search range of each variable.

Variables	Unit	Search Range	Resolution
Diameter of tube, Do	[mm]	7.0–13.0	0.01
Transverse pitch, Pt	[mm]	20.5–30.5	0.01
Longitudinal pitch, Pl	[mm]	13.0–32.0	0.01
Number of tube rows, N	-	2–6	1
Fin pitch, Fp	[mm]	1.0–8.5	0.01
Height of shape, H	[m]	4.5–8.0	0.01
Width of shape, W	[m]	3.0–5.0	0.01

The objective functions should satisfy the constraints indicated on Eq. (41), (42), (43), (44) and (45) (G. Xie et al., 2008).

$$\Delta P_a < 30\ Pa \quad (41)$$

$$\Delta P_w < 4500\ Pa \quad (42)$$

$$300 < Re_{D_c} < 2x10^4 \quad (43)$$

$$2300 < Re_c < 2x10^6 \quad (44)$$

$$1 < {}^{A}/_{A_{req}} < 1.2 \quad (45)$$

Table 3. indicates the parameters used for this problem.

Table 3. Parameters considerated.

Parameter	Unit	Value
Cost Per Unit Area, C_A	[$/m^2]	100
Exponent for Area, n	-	0.6
Hour of Operation, τ	[h/ano]	6500
Electricity Price, k_{el}	[$/MWh]	30
Pump Efficiency, η	-	0.5
Air Fouling Factor, R_{fa}	-	0.00035
Water Fouling Factor, R_{fc}	-	0.001
Correction Factor, F	-	0.97

For the Particle Swarm Algorithm, it is used different sizes of populations (particles) : 20k, 50k, 100k, 200k and 500k particles. For each method it is considerated 50 iterations.

6. RESULTS

Figure 2 indicates the optimization process for the total annual cost function. Table 4. indicates the results obtained for the total annual cost function.

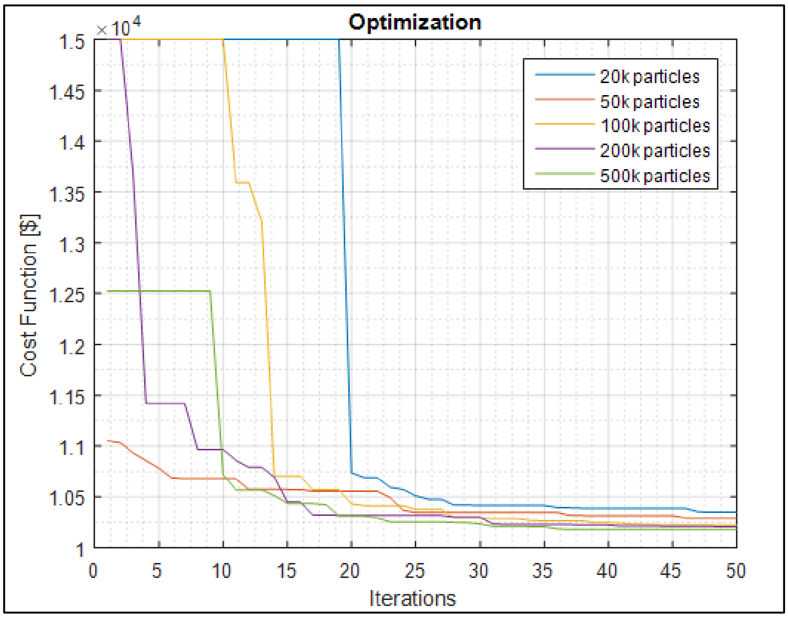

Figure 2. Optimization process for the total annual cost function.

Table 4. Results for total annual cost optimization.

Variables	**Unit**	**PSO 20k Particles**	**PSO 50k Particles**	**PSO 100k Particles**	**PSO 200k Particles**	**PSO 500k Particles**
Diameter of tube, D_0	[mm]	13	12.89	12.99	12.99	12.97
Transverse pitch, P_t	[mm]	30.38	30.47	30.17	30.48	30.5
Longitudinal pitch, P_l	[mm]	27.97	25.07	26.92	26.5	25.04
Number of tube rows, N	-	2	2	2	2	2
Fin pitch, F_p	[mm]	1.75	1.46	1.59	1.58	1.46
Height of shape, H	[m]	7.4	7.26	7.12	7.19	7.13
Width of shape, W	[m]	4.56	4.2	4.29	4.29	4.19
Total Annual Cost	**[$]**	10352.04	10288.58	10224.57	10204.49	10179.16

For the total weight funciton, Fig. (3) indicates the optimization process. Table 5. indicates the results obtained for the total weight function.

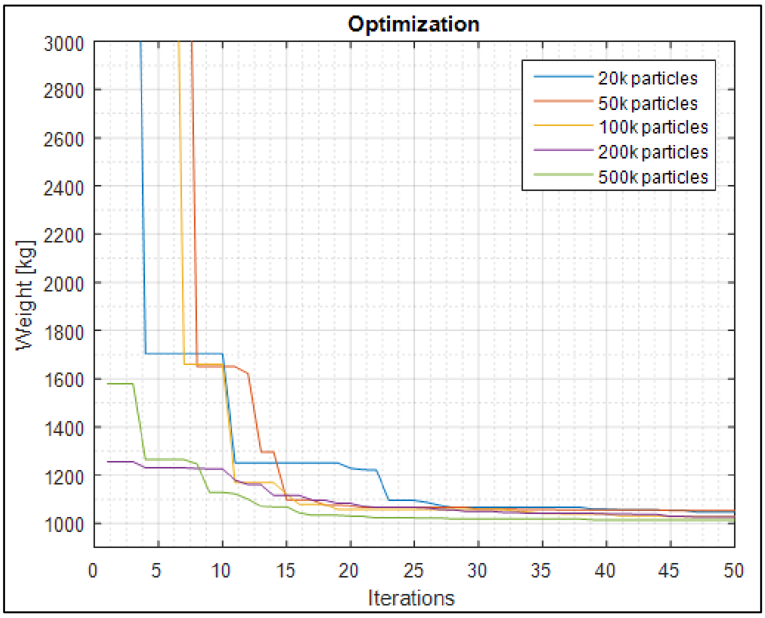

Figure 3. Optimization process for the total weitgh function.

Table 5. Results for total weight optimization.

Variables	**Unit**	**PSO 20k Particles**	**PSO 50k Particles**	**PSO 100k Particles**	**PSO 200k Particles**	**PSO 500k Particles**
Diameter of tube, D_0	[mm]	12.84	12.66	12.84	12.77	12.91
Transverse pitch, P_t	[mm]	30.27	30.46	30.48	30.44	30.48
Longitudinal pitch, P_l	[mm]	27.49	28.57	27.59	25.69	26.07
Number of tube rows, N	-	2	2	2	2	2
Fin pitch, F_p	[mm]	1.58	1.6	1.58	1.46	1.5
Height of shape, H	[m]	7.3	7.64	7.31	7.38	7.19
Width of shape, W	[m]	4.18	4.04	4.12	4.09	4.14
Total Weight	**[kg]**	1046.44	1052.71	1027.52	1026.37	1014.46

As it is possible to see, the total annual cost and the total weight decreased as the population size increased, however this change was not very significant. For the total annual cost, the results vary by 1.7% and for the total weight, 3.77%.

Thus, it was not verified a very high sensitivity of the decrease in functions in relation to the quantity of particles (population size) of the PSO algorithm.

In order to evaluate the PSO algorithm, a comparison with the Genetic Algorithm Method was made. For the comparison, the best result of the PSO (500k particles) was used. In this case, equivalent parameters for the GA were considered: 500k individuals and 50 generations. Table 6. indicates the comparison between the methods.

Table 6. Comparison between PSO and GA.

		Total Anual Cost		Total Weight	
	Unit	**PSO 500k Particles**	**GA 500k individuals**	**PSO 500k Particles**	**GA 500k individuals**
Diameter of tube, D_0	[mm]	12.97	13	12.91	13
Transverse pitch, P_t	[mm]	30.5	30.5	30.48	30.49
Longitudinal pitch, P_l	[mm]	25.04	25.8	26.07	25.8
Number of tube rows, N	-	2	2	2	2
Fin pitch, F_p	[mm]	1.46	1.5	1.5	1.5
Height of shape, H	[m]	7.13	7.07	7.19	7.07
Width of shape, W	[m]	4.19	4.18	4.14	4.18
Total Annual Cost	**[$]**	10179.16	10138.22	-	-
Total Weight	**[kg]**	-	-	1014.46	1008.06

As it is possible to see, the optimal values acquired with the PSO algorithm were very similar with the ones found by the GA method. The results were also compatible with the work of Xie et al. (2008), even though the model used in this paper is slightly different. These results indicate a good performance of the PSO algorithm for the optimization of the proposed functions. The time consumed between the methods was also evaluated as presented in Fig. (4).

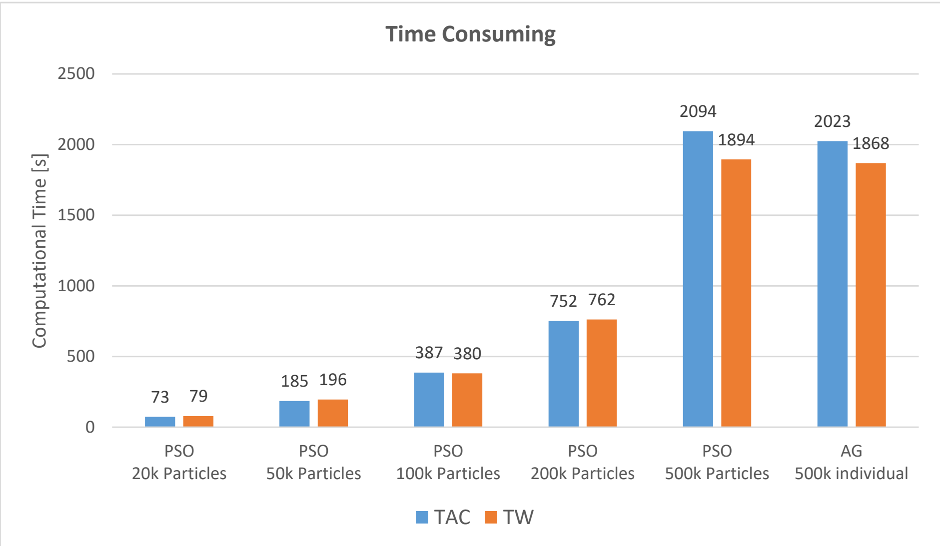

Figure 4. Comparison of the time consuming.

It is possible to verify that as the number of individual in the population increases, the time increases by almost the same proportion. Comparing the PSO algorithm and the GA algorithm, it can be noticed that both were very similar in terms of time consuming.

7. CONCLUSION

With the present work it was possible to apply the thermal design of fin-and-tube heat exchangers using particle swarm optimization considering two objective functions: the total annual cost and the total weight. In order to verify the influence of the population size in the PSO algorithm, five methods were used, varying the population size, namely: 20k, 50k, 100k, 200k and 500k particles. The results indicated low sensitivity to the population size for both objective functions.

A comparison was also made with the Genetic Algorithm method with equivalent parameters. The results found with the PSO proved to be compatible with the GA, thus presenting a good performance. It was also possible to verify the time consumed by each algorithm and it was found that as the number of individual in the population increases, the time increases by almost the same proportion. In addition, that GA had a very similar time consumed to the PSO.

In general, with the present work it was possible to apply and validate the use of the PSO algorithm in the thermal design of fin-and-tube heat exchangers.

8. REFERENCES

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