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MULTIOBJECTIVE OPTIMIZATION OF PLATE-FIN HEAT EXCHANGER BY TSALLIS DIFFERENTIAL EVOLUTION

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Abstract. *Plate-fin heat exchangers are used in several industrial processes, especially in gas-to-gas applications such as cryogenics, micro-turbines, automobiles, chemical process plants, naval and aeronautical. To deal with conflicting objectives the multiobjective optimization is presented as an important tool for researchers, scientists and engineers. This work proposes a multiobjective application of a recent variant of differential evolution for the search of better and more reliable Pareto front solutions. Simulation results show the potential of the proposed method regarding the design of a plate-fin heat exchanger with two conflicting objectives. It has been observed that the multiobjective technique of the differential evolution variant presented better results for several evaluation metrics applied in comparison to the classical multiobjective differential evolution technique and the reference method of Non-Dominated Sorting Genetic Algorithm II. In comparison to the NSGA-II technique, MOTDE presented significant increase of capacity, diversity and convergence diversity. In comparison to the original MODE, MOTDE presented better capacity and diversity.*

Keywords: *multiobjective optimization, plate-fin heat exchanger, differential evolution, cost, entropy generation units.*

1. INTRODUCTION

Cross-flow plate-fin heat exchangers are used in several industrial processes, especially in gas-to-gas applications such as cryogenics, micro-turbines, automobiles, chemical process plants, naval and aeronautical applications and presents some important characteristics that may be considered by any designer such as high thermal conductivity, large heat transfer surface area per unit of volume and high thermal effectiveness that determinate a reduction of space and energy requirement, weight and cost (Rao and Patel, 2010; Xie *et al.*, 2008; Mishra *et al.* 2009).

There are many works about single and multiobjective optimization of plate-fin heat exchangers where must be cited the works of Sanaye and Hajabdollahi (2010), using Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and Najafi *et al.* (2011), using Genetic Algorithm (GA), where were aimed the minimization of cost and maximization of efficiency.

Many real-world problems require the fulfillment of a set of requirements and specifications during its optimization processes. These engineering designs aim to find a way to satisfy our needs, keeping in account a series of conflicting objectives may exist. They require a plan that consists in problem definition, conceptualization, embodiment and detailing (Huang *et al.* 2006). These conflicting objectives may not only be inside a specific area, as they can be engineering aspects or operational cost or even safety issues.

In most multiobjective optimization all the objectives are significant to the designer, and as a consequence, each one is optimized. Generally, there are no single solution that completely satisfies all the objectives. This set of optimal solutions in the design space are called Pareto set and the region defined by the performances linked to be set of decision variables found is called Pareto front (Blasco *et al.*, 2008). Although, it is needed some criteria for the identification of the solutions that truly form the Pareto front. After the optimization process become important to measure how adequate are the obtained solutions, where performance metrics become an important field of research to develop reliable techniques to allow the scientific community the comparison between methods of multiobjective optimization. Between measurement metrics are Overall Non-dominated Vector Generation (ONVG) and Hypervolume (HYP) (higher values better), Spacing (S) (lower values better) which description can be found in Jiang *et al.* (2014).

In this paper, a multiobjective version of the Tsallis differential evolution (TDE) is proposed and its optimization results compared to differential evolution (DE) (Reynoso-Meza *et al.*, 2010) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II).

2. COMPUTATIONAL PROCEDURE

The study case considers heat exchange between gas-to-air and ideal gases and was taken from Mishra et al. (2009) where the heat duty is approximately 160 kW where the objective function were minimization of cost and minimization of entropy generation units. The following lower and upper bounds for the optimization variables were imposed: the heat exchanger length for hot and cold fluids ranging from 0.1 m to 1.0 m; the height of fin ranging from 0.002 m to 0.01 m; the fin frequency ranging from 100 to 1000; the fin thickness ranging from 0.0001 m to 0.0002 m; the lance length of the fin ranging from 0.001 m to 0.01 m; and the number of fin layers for the hot fluid ranging from 1 to 10. The heat transfer model for plate-fin heat exchanger can be found in Rao and Patel (2010). The description of the proposed technique, Tsallis differential evolution, can be found in Vasconcelos Segundo *et al.* (2017a).

The Table 1 presents the process input and l properties of the case study (Xie *et al.*, 2008; Mishra *et al.* 2009).

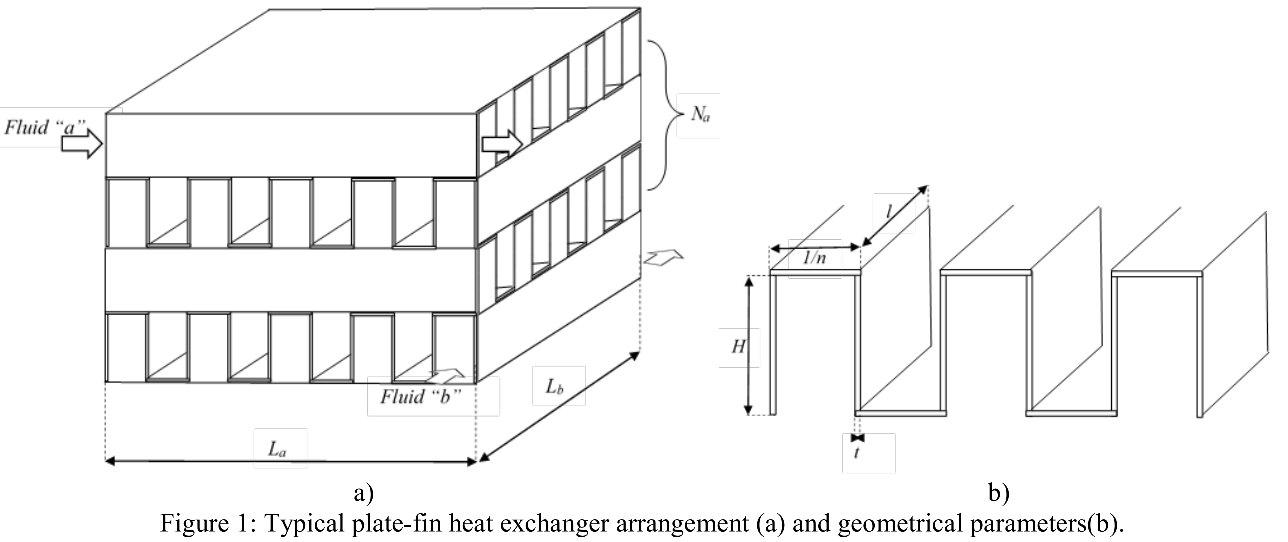
Table 1: The process input and physical properties for the case study.

	Hot fluid (a)	Cold fluid (b)
m (kg/s)	0.8962	0.8296
T_i (K)	513	277
P_i (Pa)	100000	100000
cp (J/kg K)	1012.7	1011.8
ρ (kg/m³)	0.8186	0.9385
μ (Ns/m²)	0.002410	0.002182
Pr	0.6878	0.6954
τ (h.y^{-1})	6500	
k_{el} (\$.MWh^{-1})	30	
η	0.5	

The following sections present a description of the heat exchanger model, of the proposed algorithm and for the multiobjective evaluation metrics used for the performance analysis of the simulations.

2.1 Plate-Fin Heat Exchanger Model

The following calculations were taken from Zarea *et al.* (2014) and Mishra *et al.* (2009). The Figure 1 present the typical configuration of a plate-fin heat exchanger.



a) b)

Figure 1: Typical plate-fin heat exchanger arrangement (a) and geometrical parameters(b).

Considering a cross-flow plate-fin heat exchanger with both fluids unmixed, the heat transfer rate is calculated by Eq. (1),

$$Q = \varepsilon C_{\min}(T_{hi} - T_{ci}) \quad (1)$$

where ε is the effectiveness, C_{min} is the minimum heat capacity rate and T_{hi} and T_{ci} are the inlet temperatures of the hot and cold fluids, respectively.

The effectiveness is given by Incropera (2010) by Eq. (2),

$$\varepsilon = 1 - e^{(Cr^{-1} NTU^{0.22}(e^{(-CrNTU^{0.78})} - 1))} \quad (2)$$

where $Cr = C_{\min} / C_{\max}$ and NTU is the number of transfer units determined from the Eq. (3),

$$\frac{1}{NTU} = C_{\min}\left(\frac{Aff_h}{j_h cp_h \Pr_h^{-0.667} m_h A_h} + \frac{Aff_c}{j_c cp_c \Pr_c^{-0.667} m_c A_c}\right) \quad (3)$$

where Aff is the free flow area, A is the heat transfer area, j is the Colburn factor, cp is the specific heat and Pr is the Prandtl number for each fluid, hot and cold.

The free flow areas can be obtained from Eq. (4) and Eq. (5),

$$Aff_h = (H_h - t_h)(1 - n_h t_h) L_c N_h \quad (4)$$

$$Aff_c = (H_c - t_c)(1 - n_c t_c) L_h N_c \quad (5)$$

where H is the height of the fin, t is the fin thickness, n is the fin frequency, L is the heat exchanger length and N is the number of fin layers for each fluid, remembering that $N_c = N_h + 1$.

The heat exchangers areas are given by Eq. (6) and Eq. (7),

$$A_h = L_h L_c N_h (1 + (2 n_h (H_h - t_h))) \quad (6)$$

$$A_c = L_c L_h N_c (1 + (2 n_c (H_c - t_c))) \quad (7)$$

where the total heat exchanger area $A_{tot} = A_h + A_c$.

The Colburn factor is determined by Eq. (8),

$$j = \begin{cases} 0.53 \mathrm{Re}^{-0.5} \left(\frac{l}{dh}\right)^{-0.15} \left(\frac{s}{H - t}\right)^{-0.14}, \mathrm{Re} \le 1500 \\ 0.21 \mathrm{Re}^{-0.4} \left(\frac{l}{dh}\right)^{-0.24} \left(\frac{t}{dh}\right)^{-0.02}, \mathrm{Re} > 1500 \end{cases} \quad (8)$$

where Re is the Reynolds number, l is the lance length of the fin, dh is the hydraulic diameter and the fin spacing $s = t - 1/n$ for hot and cold fluids.

The Reynolds number for each fluid of the system can be obtained from Eq. (9),

$$\mathrm{Re} = \frac{mdh}{Aff\mu} \quad (9)$$

where m is the mass flow rate and μ is the viscosity of each fluid, remembering that $G = m / Aff$.

The hydraulic diameter can be determined for both fluids by Eq. (10),

$$dh = \frac{2(s-t)(H-t)}{s+(H-t)+(\frac{Ht-t^2}{l})} \tag{10}$$

Also, the frictional pressures drops for the two streams are given by Eq. (11) and Eq. (12),

$$\Delta P_h = \frac{2 f_h m_h^2 L_h}{\rho_h dh_h L_c^2 N_h^2 (H_h - t_h)^2 (1-n_h t_h)^2} \tag{11}$$

$$\Delta P_c = \frac{2 f_c m_c^2 L_c}{\rho_c dh_c L_h^2 N_c^2 (H_c - t_c)^2 (1-n_c t_c)^2} \tag{12}$$

where f is the fanning friction factor, determined by Eq. (13),

$$f = \begin{cases} 8.12\,\mathrm{Re}^{-0.74}(\frac{l}{dh})^{-0.41}(\frac{s}{H-t})^{-0.02}, \mathrm{Re} \leq 1500 \\ 1.12\,\mathrm{Re}^{-0.36}(\frac{l}{dh})^{-0.65}(\frac{t}{dh})^{-0.17}, \mathrm{Re} > 1500 \end{cases} \tag{13}$$

The convective heat transfer coefficient for both fluid can be determined by Eq. (14),

$$h = jcp\,\mathrm{Pr}^{-2/3}\frac{m}{Aff} \tag{14}$$

The outlet pressures and temperatures are given by Eq. (15), Eq. (16), Eq. (17) and Eq. (18),

$$P_{ho} = P_{hi} - \Delta P_h \tag{15}$$

$$P_{co} = P_{ci} - \Delta P_c \tag{16}$$

$$T_{ho} = T_{hi} - (\varepsilon \frac{C_{\min}}{C_{\max}}(T_{hi} - T_{ci})) \tag{17}$$

$$T_{co} = T_{ci} + (\varepsilon \frac{C_{\min}}{C_{\max}}(T_{hi} - T_{ci})) \tag{18}$$

for both fluids.

2.2 Objective Functions

The objective functions for the plate-fin heat exchanger were the total cost, given in $, and the entropy generation units, dimensionless.

The total cost can be obtained by Eq. (19) and Eq. (20) taken from Xie *et al.* (2008):

$$Ci = 100 A_{tot}^{0.6} \tag{19}$$

$$Cop = k_{el}\tau\frac{\Delta Pa}{\eta} + k_{el}\tau\frac{\Delta Pb}{\eta} \tag{20}$$

where k_{el} is the electricity cost ($\$.MW^{-1}h^{-1}$), τ is the hours of operation ($h.y^{-1}$) and η is the pump efficiency.

Accordingly to the methodology found in Rao and Patel (2010) the entropy generation units, *Ns*, for two fluids can be expressed in terms of the temperature and pressure drop, given by Eq. (21), Eq. (22) and Eq. (23):

$$Ns_a = \frac{Ca}{C_{\max}}(\ln(1-\varepsilon\frac{C_{\min}}{Ca}(1-\frac{Tb_i}{Ta_i})) - \frac{Ra}{cpa}\ln(1-\frac{\Delta Pa}{Pa_i})) \tag{21}$$

$$Ns_b = \frac{Cb}{C_{\max}}(\ln(1-\varepsilon\frac{C_{\min}}{Cb}(\frac{Tb_i}{Ta_i}-1)) - \frac{Rb}{cpb}\ln(1-\frac{\Delta Pb}{Pb_i})) \tag{22}$$

$$Ns = Ns_a + Ns_b \tag{23}$$

where Ta_i, Tb_i, Ta_o e Tb_o are the inlet and outlet temperature of the system (K), Pa_i and Pb_i are the inlet pressure (Pa), ΔPa and ΔPb are the pressure drops (Pa), *cpa* and *cpb* are the specific heat ($J.kg\text{-}1.K^{-1}$), *Ra* and *Rb* are the gas constants ($J.kg\text{-}1.K^{-1}$), and C_{max}, C_{min}, *Ca* and *Cb* are the maximum, minimum and fluidic heat transfer rate ($W.K^{-1}$).

2.3 Tsallis Differential Evolution

The Differential Evolution variant, denominated as Tsallis Differential Evolution, performs a self-adaptation of the scale factor *F* in the original algorithm using the Tsallis Distribution (Tsallis, 1988) using Eq. (25), Eq. (26) and Eq. (27).

$$P_q = A_q(1+(q-1)B_q(x-\mu_q)^2)^{1/1-q} \tag{25}$$

$$A_q = \frac{\Gamma(\frac{1}{q-1})}{\Gamma(\frac{3-q}{2q-2})}\sqrt{\frac{q-1}{\pi}B_q} \tag{26}$$

$$Bq = ((3-q)\sigma^2)^{-1} \tag{27}$$

where *q* is the first distribution control parameter linked to the type of distribution that assumes values from 1 to 3. Values of *q* close to 1 performs a Gaussian distribution, values of *q* close to 2 performs a Lorentzian distribution and values of *q* close to 3 perform a Lévy distribution.

The normalization constant A_q and B_q are the second distribution control parameters linked to the height and width of the distribution. The mean of the distribution is μ_q and the variance of the distribution is σ^2_q.

For each population member, a random value of *q* was generated for the determination of the distribution. This procedure is loop until the stopping criteria.

That means that the value of the scale factor *F* is determined in TDE by Eq. (28),

$$F = F_\mu + F_{\sigma^2}(\frac{\Gamma(\frac{1}{q-1})}{\Gamma(\frac{3-q}{2q-2})}\sqrt{\frac{q-1}{\pi(3-q)F_{\sigma^2}}}(1+\frac{(q-1)(F_0-F_\mu)^2}{(3-q)F_{\sigma^2}})^{1/1-q}) \tag{28}$$

at each generation where F_0 is the initialization of the factor scale.

The Figure 2 presents the steps for the DE and for the TDE algorithm highlighting the difference between both techniques.

Differential Evolution	*Tsallis Differential Evolution*
Step 1. Select NP individuals x_i^G randomly.	**Step 1.** Select NP individuals x_i^G randomly.
Step 2. For $i = 1$ to NP let $f_1 = f(x_i^G)$	**Step 2.** For $i = 1$ to NP let $f_1 = f(x_i^G)$ with initial F_0
Step 3. While convergence criterion not met do steps 4 to 10	**Step 3.** While convergence criterion not met do steps 4 to 10
Step 4. For $i = 1$ to NP do steps 5 to 10	**Step 4.** For $i = 1$ to NP do steps 5 to 10
Step 5. Select three different random individuals x_{r1}, x_{r2}, x_{r3} between 1 to $NP(i \neq r1 \neq r2 \neq r3)$	**Step 5.** Select three different random individuals x_{r1}, x_{r2}, x_{r3} between 1 to $NP(i \neq r1 \neq r2 \neq r3)$
Step 6. Let $v_1^{G+1} = x_{r1}^G + F(x_{r2}^G - x_{r3}^G)$	**Step 6.** Let $v_1^{G+1} = x_{r1}^G + F(x_{r2}^G - x_{r3}^G)$ where $F = \overline{F} + F_{\sigma^2} P_q$
Step 7. For $j = 1$ to D do steps 8 to 9	**Step 7.** For $j = 1$ to D do steps 8 to 9
Step 8. Select randomly $rand(j)$ variable ($0 < rand(j) < 1$) and $jrand(1 \leq jrand \leq D)$	**Step 8.** Select randomly $rand(j)$ variable ($0 < rand(j) < 1$) and $jrand(1 \leq jrand \leq D)$
Step 9. If $rand(j) \leq CR$ or $j = rand(i)$ then $u_1^{G+1} = v_{ij}^{G+1}$ else $u_1^{G+1} = x_{ij}^{G+1}$	**Step 9.** If $rand(j) \leq CR$ or $j = rand(i)$ then $u_1^{G+1} = v_{ij}^{G+1}$ else $u_1^{G+1} = x_{ij}^{G+1}$
Step 10. If $f(u^{G+1}) \leq f(x_1^G)$ then $x_1^{G+1} = u_1^{G+1}$ else $x_1^{G+1} = x_1^G$	**Step 10.** If $f(u^{G+1}) \leq f(x_1^G)$ then $x_1^{G+1} = u_1^{G+1}$ else $x_1^{G+1} = x_1^G$

Figure 2: Steps for the DE and for the TDE algorithm.

It can be seen that the major difference consists in the determination of the factor scale in sixth step where the Tsallis distribution is applied where the random generation of the q value performs a wide chance of different distributions to be generated at each iteration of the optimization process, enhancing the chance of reach values for the factor scale that can achieved better results.

2.4 Multiobjective Evaluation Metrics

In the design of multi-objective metrics, three major performance criteria, namely capacity, convergence and diversity, have typically been taken into considerations. Based on these considerations multi-objective metrics can be categorized into four groups (Jiang *et al.* 2014):

a) Capacity metrics: these metrics quantifies the number of non-dominated solutions;

b) Convergence metrics: these are metrics for measuring the proximity of optimal solution set;

c) Diversity metrics: these metrics include two forms of information, i.e., distribution (that measures how evenly scattered are the solutions in the objective space) and spread (that indicates how well do the solutions arrive at the extrema of true Pareto front, or ideal Pareto front);

d) Convergence–Diversity metrics: these metrics indicates both the convergence and diversity on a single scale.

The evaluation of multiobjective optimization results can be done from the point-of-view of capacity, diversity and convergence-diversity properties. All the next expressions and explanations was taken from Jiang *et al.* (2014).

Capacity metrics quantify the number, or ratio, of non-dominated solutions in the optimal solution set (S) that conforms to the predefined requirements. A large number of non-dominated solutions is commonly preferred. The Overall Non-dominated Vector Generation (ONVG) is given by Eq. (29):

$$ONVG(S) = |S| \tag{29}$$

where |.| defines the cardinality, or number of elements in the set, unless explicitly indicated. This metric gives the number of non-dominated solutions in the optimal set (S).

Diversity metrics indicate the distribution and spread of solutions in the optimal set (S). The Spacing (SP) metric is given by Eq. (30):

$$SP = \sqrt{\frac{\sum_{i=1}^{|S|} (d_i - d)^2}{(|S| - 1)}} \tag{30}$$

where d_i is the smallest distance between the Pareto set to the closest solution in the optimal set S. Here, again, the Euclidian distance is applied, unless explicitly indicated.

The convergence-diversity metric measures the quality of the optimal solution set S in terms of convergence and diversity on a single scale. Two of the most commonly used metric are the Hypervolume (HV), given by Eq. (31):

$$HV(S) = volume(\bigcup_{i=1}^{|S|} v_i) \quad (31)$$

where the Hypervolume is the are given by the enclosed discontinuous boundary given for each feasible solution, being that for each solution in S a hypercube v_i is constructed with the reference set and the solution as the diagonal corners of the hypercube.

In this study, the metrics of Spacing and Hypervolume were calculated using normalized values for the Pareto front non-dominated solutions, procedure that reduce scale differences and allow a better comparison about the performance of the algorithms.

3. RESULTS AND DISCUSSION

Previous works about the optimization of plate-fin heat exchanger using only one objective function. For example, Mishra *et al.* (2009), Rao and Patel (2010), Zarea *et al.* (2014) and Vasconcelos Segundo *et al.* (2017b) investigated the entropy generation units minimization by several techniques and reached values of 0.063332, 0.053028, 0.052886 and 0.046688, respectively. The total annual cost objective function was also studied by Xie *et al.* (2008) and Rao and Patel (2010) where values close to 3050 and 3020 $ were obtained, respectively.

The values presented previously can serve as a basis to understand the results of the multiobjective optimization for both total annual cost and entropy generations units regarding the fact that these functions are conflicting, i.e, lower values of total annual cost contemplate higher values of entropy generation units and vice-versa.

The Figure 2 presents the Pareto front for the reference technique, NSGA-II, classical differential evolution in multi-objective version and proposed technique, also in multi-objective version, considering the non-dominated points achieved from 30 independent runs where f_1 and f_2 are the total annual cost and the entropy generation units, respectively.

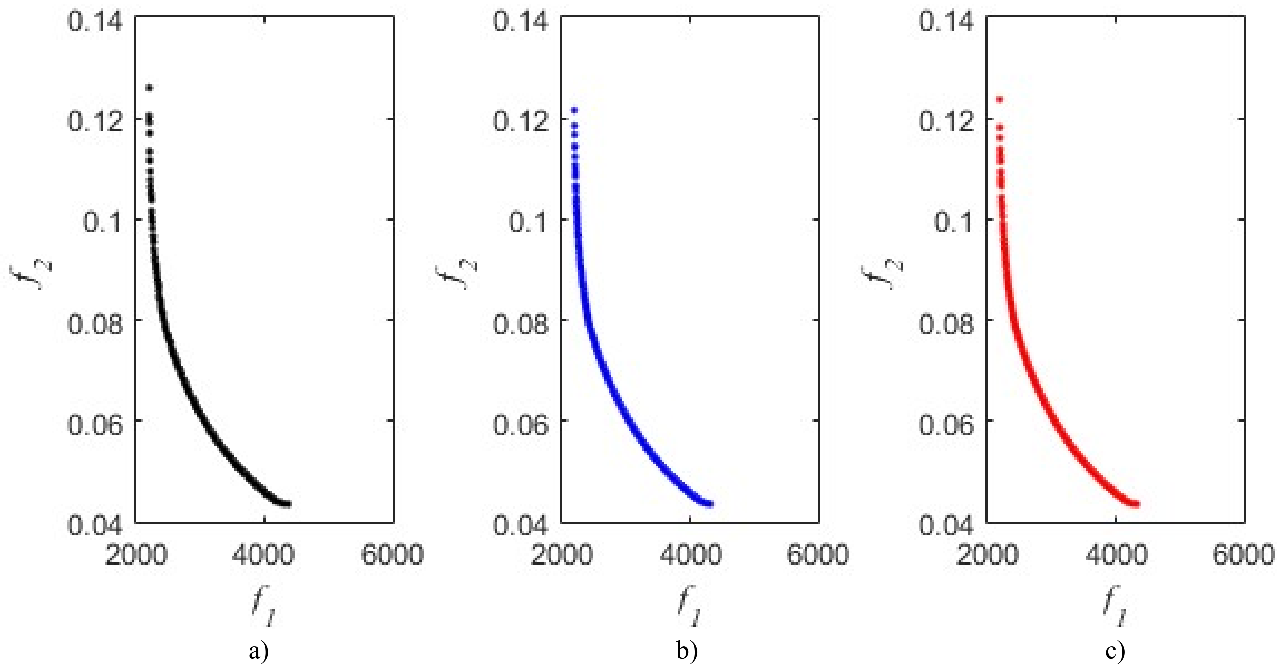


Figure 2: Pareto fronts for NSGA-II (a), Multi-Objective Differential Evolution (b) and Multi-Objective Tsallis Differential Evolution (c) for the 30 independent runs non-dominated solutions.

It can be observed from the Figure 3 that the values for the total annual cost were between 2000 and 4500 $ and the values for the entropy generation units were between 0.04 and 0.13. That corroborates the conflicting behavior of both objective functions and converge in isolation for the results of previous works mentioned.

Although the simulations seem similar they differ in some characteristics that will be discussed below in the performance metrics for multiobjective evaluation in relation to the capacity, diversity and convergence-diversity.

Table 2 presents the results for capacity (ONVG), diversity (SP) and convergence-diversity (HV) metrics of evaluation for each one of the techniques applied to the plate-fin heat exchanger multiobjective optimization for the non-dominated solutions obtained.

The results obtained shows that the proposed technique (MOTDE) presented better results in two of three multiobjective metrics of evaluation performed, Overall Non-dominated Vector Generation and Spacing in comparison to the classical differential evolution in multi-objective version (MODE), and in all metrics when in comparison to the reference method Non-Dominated Sorting Genetic Algorithm II.

Table 2 – Results of the multiobjective evaluation metrics.

	NSGA-II	*MODE*	*MOTDE*
ONVG	265	768	795
SP	0.0333	0.0186	0.0178
HV	0.2609	0.2630	0.2630

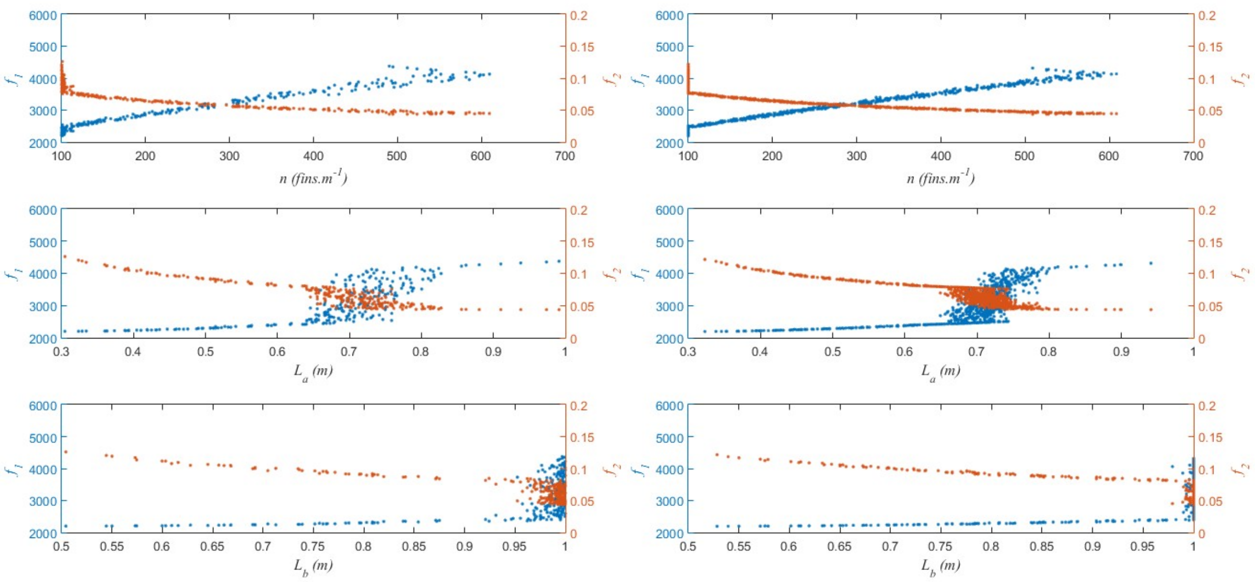
Major difference were obtained for the capacity metric while minor increase are observed in the convergence-diversity evaluation and convergence-diversity metric of Hypervolume. For the capacity an increase of 200% was observed for the Multi-Objective Tsallis Differential Evolution in comparison to the reference method Non-Dominated Sorting Genetic Algorithm II, while 3.5% was achieved in comparison to the classical differential evolution technique.

The diversity were also enhanced for the Multi-Objective Tsallis Differential Evolution in comparison to the others algorithms reaching reductions of 46.5% and 4.3% against the results of Non-Dominated Sorting Genetic Algorithm II and Multi-Objective Differential Evolution, respectively. The convergence-diversity metric for Multi-Objective Differential Evolution and Multi-Objective Tsallis Differential Evolution presented equivalent results, but increases in relation to the Non-Dominated Sorting Genetic Algorithm II in about 1%.

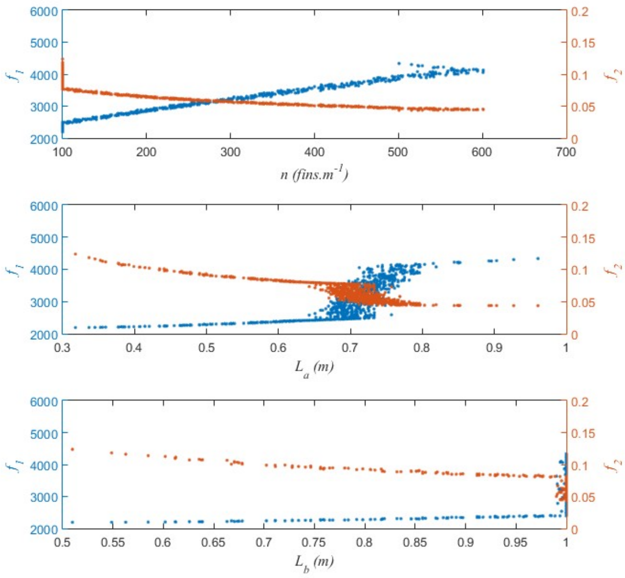
The Figure 3 shows the three variables that presented variation amongst the original seven decision variables. All the three methods presented similar behavior in the variables distributions and tendencies, showing clearly that those parameters have inverse relations with each one of the objective functions.

For the density of fins, *n*, the values obtained were between 100 and 600 fins.m^{-1} where an increase of the density of fins causes a reduction in the entropy generations units and an increase in the total annual cost. Also, for both lenght of the heat exchanger for hot and cold fluids, increases in the values for these variables leed to a increases in the total annual cost and in a reduction of the entropy generation units, where for L_a were reached values between 0.3 and 1 m and for L_b values between 0,5 and 1 m.

The remaining variables presented values close to 0.01 m for the height of the fin, 0.001 for the fin thickness, 0.01 for the lance length of the fin and 10 for the number of fin layers. A thermal evaluation was also obtained were the principal parameters evaluated were the heat transfer coefficients, pressure drops and Reynolds number for both fluids and total heat exchanger area and efficiency.



a) b)



c)

Figure 3: Decision variables that presented variation for NSGA-II(a), MODE(b) and MOTDE(c) for the 30 independent runs non-dominated solutions.

Similar behaviours were reached for the heat transfer coefficients and Reynolds numbers for both fluids, also for the total heat exchanger areas and efficiency, while distinct behaviours were achieved for the pressure drops for each fluid.

The Table 3 presents the parameters and their lower and higher values for the thermal analysis.

Table 3 – Results of the heat transfer coefficients, Reynolds numbers and pressure drops for both fluid, total heat exchanger area and efficiency.

	Lower value	Higher value
h_a (W.m^{-2}.K^{-1})	770	1100
h_b (W.m^{-2}.K^{-1})	720	1200
Re_a	110	230
Re_b	110	350
ΔP_a (Pa)	1600	2820
ΔP_b (Pa)	2000	3900
A (m²)	9.5	221
ε (%)	27	79

Simulations showed that higher values of the heat transfer coefficients for both fluids accompany lower values for the total annual cost and higher values for the entropy generation units, and the same are observed for he Reynolds numbers.

About the pressure drops, higher values for the hot fluid leads to higher total annual cost and lower entropy generation units, while for the cold fluid an inverse relation was obtained, with lower values accompanying higher total annual cost and lower entropy generation units.

For both total heat exchanger surface area and efficiency, higher values accompany higher total annual cost and lower entropy generation units.

4. CONCLUSIONS

In this paper, the proposed Multi-Objective Tsallis Differential Evolution (MOTDE) algorithm has been sucessfully implemented to solve a multiobjective optimization regarding a plate-fin heat exchanger for a case study widely explored in the literature by several methods. Simulation results show the potential of the MOTDE as a powerful and efficient search technique for problems with conflicting objectives. In comparison to the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) technique the proposed method presented significant enhance of capacity (200%), diversity (46.5%) and convergence-diversity (1%) was reached and, in comparison to the original algorithm Multi-Objective Differential Evolution (MODE) MOTDE presented enhance in capacity (3.5%) and diversity (4.3%), reaching the same convergence-diversity result.

The simulations showed that only three of seven decision variables trully presented variation. For the density of fins, *n*, the values obtained were between 100 and 600 fins.m^{-1} where an increase of the density of fins causes a reduction in the entropy generations units and an increase in the total annual cost. Also, for both lenght of the heat exchanger for hot and cold fluids, increases in the values for these variables leed to a increases in the total annual cost and in a reduction of the entropy generation units, where for L_a were reached values between 0.3 and 1 m and for L_b values between 0,5 and 1 m. The remaining variables presented values close to 0.01 m for the height of the fin, 0.001 for the fin thickness, 0.01 for the lance length of the fin and 10 for the number of fin layers.

About the thermal analysis the simulations showed that higher values of the heat transfer coefficients for both fluids accompany lower values for the total annual cost and higher values for the entropy generation units, and the same are observed for he Reynolds numbers. About the pressure drops, higher values for the hot fluid leads to higher total annual cost and lower entropy generation units, while for the cold fluid an inverse relation was obtained, with lower values accompanying higher total annual cost and lower entropy generation units. For both total heat exchanger surface area and efficiency, higher values accompany higher total annual cost and lower entropy generation units.

5. ACKNOWLEDGEMENTS

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7. RESPONSIBILITY NOTICE