A NEW EVOLUTIONARY ALGORITHM FOR MULTIOBJECTIVE OPTIMIZATION BASED ON ENDOCRINE PARADIGM

by
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Abstract: Multiobjective optimization problems, due to their complexity, are suitable for interesting evolutionary approaches. Many evolutionary algorithms have been developed for solving multiobjective problems, appealing or not to the Pareto optimality concept. Although, evolutionary techniques for multiobjective optimization confront with several issues as: elitism, diversity of the population, or efficient settings for the specific parameters of the algorithm. In this paper, we propose a new evolutionary technique, which is inspired by the behavior of the endocrine system and uses the Pareto non-dominance concept. Therefore, the population's members are no more called chromosomes but hormones and even if they evolve according to the genetic principles (selection, crossover, and mutation), a supplementary mechanism, based on the endocrine paradigm, is connected with standard approach to deal with multiobjective optimization problems. Moreover, the proposed algorithm, in order to maintain population's diversity, uses a specific scheme of fitness sharing, eliminating the inconvenient of defining an appropriate value of sharing factor.
Keywords: multiobjective optimization, endocrine paradigm, evolutionary algorithm.

1. Introduction

Multiobjective optimization (MOO) occupies a large area in technical literature. The optimization problems became difficult in more than a single objective's cases, so, the optimum concept is reformulated accordingly. Vilfredo Pareto offers the most common definition of optimum in multiobjective optimization (1896). The evolutionary techniques, which make use of Pareto concept of optimality, are so called Pareto-based approaches and were firstly suggested by Goldberg (1989). Since then, many Pareto-based evolutionary techniques have been developed for multiobjective optimization problems.

Our paper proposes a new evolutionary algorithm for multiobjective optimization based on endocrine paradigm. Evolutionary algorithms for MOO deal with specific issues as fitness assignment, diversity preservation or elitism. We also suggest in our paper a new paradigm, which could be a fruitful source of inspiration for evolutionary computation: endocrine paradigm. This natural system proves itself as a complex, semi-independent and adaptive system – qualities that could be exploited in evolutionary techniques.

2. Statement of the Problem

Multiobjective optimization problems, also called multicriterial optimization problems – MOPs, involves the search of the optimum solutions according with more than one criterion. Generally, those criteria are conflicting and this fact makes the MO problems to be difficult. Formally, MOP is given as follows: Considering *m* inequality constrains (*2*), *p* equality constrains (*3*) and *k* criteria (*1*), we are interested in finding the decision variable vector in the domain *D*, $D \subset R^n$: $\overline{x^*} = \left(x_1^*, x_2^*, ..., x_n^*\right)$, which optimizes the vector function (*1*), and satisfies the constrains (*2*) and (*3*):

$$F(\overline{x}) = \overline{f}(\overline{x}) = \left(f_1(\overline{x}), f_2(\overline{x}), ..., f_k(\overline{x})\right) \quad (1)$$

$$g_i(\overline{x}) \geq 0,\ i = 1,2,\dots,m \quad (2), \quad h_i(\overline{x}) = 0,\ i = 1,2,\dots,p \quad (3)$$

Since, we hardly ever detect a real-world situation where all the objective functions have the same optimum in the search space *D*, the concept of optimality should have been revised in the multiobjective optimization's context.

3. Pareto Optimality

Vilfredo Pareto formulated the most common concept of optimality for multicriterial optimization problems. In order to estimate the quality of a particular element from the search space, a relation of dominance was established. We consider a *k*-objective minimization problem and a search domain *D*, $D \subset R^n$.

Definition 1: We state that the vector $a = \left(a_1, a_2, ..., a_k\right)$ *dominates* the vector $b = \left(b_1, b_2, ..., b_k\right)$ if and only if the following assertion if verified:

$$(\forall i \in \{1,2,...,k\} : a_i \leq b_i) \wedge (\exists i \in \{1,2,...,k\} : a_i < b_i) \quad (4)$$

Definition 2: We state that the solution $x \in D$ is *weakly non-dominated*, if:

$$\neg\exists y \in D \ for\ which\ \forall i \in \{1,2,...,k\} : b_i < a_i \quad (5),$$

where $f(y) = (b_1, b_2, ..., b_k)\ and\ f(x) = (a_1, a_2, ..., a_k)$.

Definition 3: We state that the solution $x \in D$ is *strongly non-dominated*, if:

$$\neg\exists y \in D \ for\ which\ (\forall i \in \{1,2,...,k\} : b_i \leq a_i) \wedge (\exists i \in \{1,2,...,k\} : b_i < a_i) \quad (6)$$

where $f(y) = (b_1, b_2, ..., b_k)\ and\ f(x) = (a_1, a_2, ..., a_k)$.

Definition 4: We state that the solution $x \in D$ is *Pareto optimal* if and only if the next assertion is verified:

$$\neg\exists\ y \in D \ for\ which\ f(y) = (b_1, b_2, ..., b_k)\ dominates\ f(x) = (a_1, a_2, ..., a_k) \quad (7)$$

Pareto front consists of the non-dominated vectors *f(x)* that corresponds to the Pareto optimal solutions $x,\ x \in D$. For example, an optimization problem with two objective functions: f_1 and f_2 (figure1).

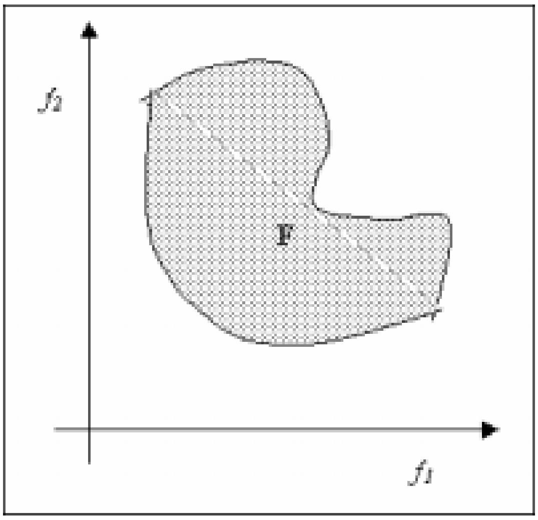

Figure 1: The Pareto front is marked with bold line

4. Diversity versus Elitism

Many researchers emphasized the importance of these two features of the evolutionary approaches in the cases of multiobjective optimization [*6*], [*7*], [*15*], [*17*]. They also developed various mechanisms for elitism and diversity preservation, which leaded to a substantial increase of the algorithms' performance.

While elitism stresses the local search – the examination of the best areas of the search space, diversity of the population guarantees an efficient exploration of the entire search space. A good equilibrium between local search and space's exploration could be maintained by the equilibrium between diversity preservation mechanism and elitism technique. The technical literature specifies how important elitism is and stresses the fact that elitist approaches offer better solutions than non-elitist approaches.

Evolutionary multiobjective optimization, due to its specificity, requires a closer attention regarding those two mentioned features. Finding multiple solutions, which are diversely distributed along the Pareto frontier, represents a difficult problem.

5. Endocrine Paradigm

Many evolutionary techniques for solving different types of problems are developed and inspired from nature (as: immune systems, ant colony, hereditary principles, and so on). Our proposed algorithm for multiobjective optimization applies several principles inspired of endocrine system. Even if endocrine system has a particular dependence of nervous system, due to the intrinsic mechanisms of control and its functions, it represents by itself a suitable paradigm in evolutionary computation's landscape.

The endocrine system, through its function and anatomy is relevant as a complex and adaptable system. That is why an artificial shaping of this one seems to be suitable for solving some complex problems.

A quick view on endocrine system reveals how complex and ingenious the nature can be.

Endocrine system is represented by a collection of glands, which produce chemical messengers called hormones. These signals get through the blood system to the target organs, which have cells containing appropriate receptors. The receptors of the cells recognize and tie one type of hormone. Hormones provoke profound changes at the level of the target cells. Every type of hormone has a specific shape, recognized only by the target cells. The main glands of endocrine system are: pituitary gland (hypophysis), thyroid gland, the pancreas, the gonads, the adrenal glands and pineal gland. Pituitary gland is considered "master gland" of the body. This description is based on the control, which this one exercises.

At the pituitary gland level are produced those hormones which influence and control the cells and the process of the organism. Its role of supervisor is offered in reality by the function of the hypothalamus, this one representing the bound between the nervous and endocrine systems. Hypothalamic neurons secrete hormones that regulate the release of hormones from the pituitary gland. Hypothalamic hormones are two types: releasing and inhibiting hormones, reflecting the influence, which they have over the producing of pituitary hormones, called tropes.

In order to better understand the self-control process of the endocrine system, the following example is taken in consideration: releasing thyroidian hormone (TRH) produced by hypothalamus actions on hypophysis determining the secretion of the thyroidian stimulation hormone (TSH). This one will act on the target organ i.e. thyroid gland. The action of TSH hormone on thyroid is concretized by the secretion of the specific thyroidian hormones. Thus, when the concentration of the specific thyroidian hormones becomes too high or too low, through a negativ feedback process, the hypothalamus is announced about this aspect. So, using inhibiting or releasing hormones the hypothalamus acts on hypophysis producing an inhibition/releasing in the production of thyroidian stimulation hormones (TSH) with a direct effect on thyroid gland activity and thus, a coming back to normal of thyroidian hormones concentration.

Concluding, the concentration of specific hormones is controlled trough a feedback mechanism. So, a special type of hormones generated by hypophysis, called tropes, have the role to supervise and to imprint the releasing or inhibiting of specific hormones. This principle is adopted in our algorithm for diversity preservation. Simplifying, endocrine system's mechanism for controlling the hormonal concentration is shown in the next figure.

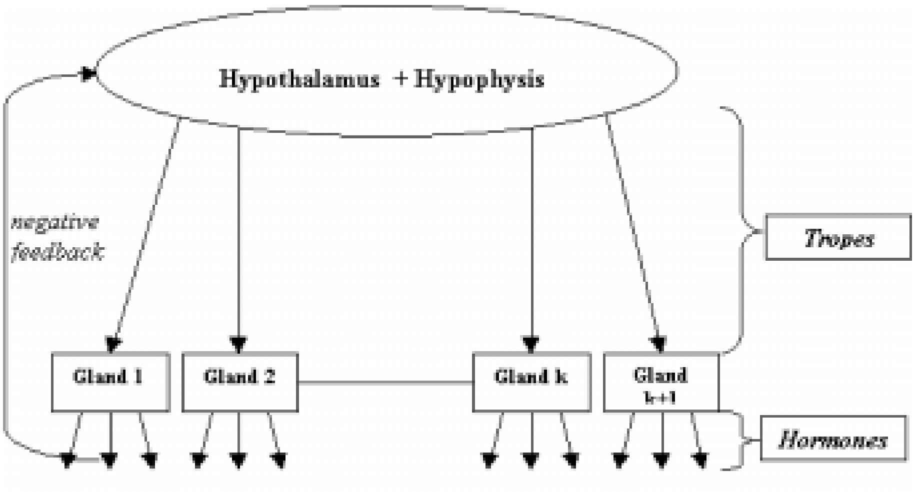

Figure 2 Control scheme of endocrine system

6. A New Evolutionary Algorithm for Multiobjective Optimization

The principle of the proposed method relies on keeping two populations: an active population of hormones, H_t, and a passive population of non-dominated solutions, A_t. The members of the passive population behave as a population of elite and also have a supplementary function: to lead the hormones toward the Pareto front, keeping them as much as possible well distributed among the search space. These two populations correspond to the two classes of hormones in endocrine paradigm:

1. Specific hormones, which are released by different glands of the body – the active population H_t.
2. The hormones of control (trop), which are produced by control level of the endocrine system (hypothalamus and hypophysis) in order to supervise the density of each type of hormone - the passive population A_t.

Population of control, *A*, is modified at each generation. The new population A_{t+1} gathers all non-dominated solution from the population U_t, which has resulted from merging current population of hormones H_t and the previous population A_t.

This manner of changing the population of controllers assures us that the non-dominated solutions from the previous population A_t cannot be lost if they still remain non-dominated after the active population H_t has changed.

The passive population, A_t, doesn't suffer modification at individual's level, under the variation operators as crossover and mutation. It behaves as an elite population of non-dominated solutions from the current generation, which is only actualized at each generation. Finally, population A_t contains a predetermined number of non-dominated vectors and provides a good approximation of Pareto front.

At each generation *t*, the members of H_t are classified into *sa* classes. A corresponding controller from A_t supervises a particular class. The idea is that each hormone *h* from H_t is supervised by the nearest controller a_i from A_t:

$$C(a_i) = \{h \in H_t, dist(h, a_i) = \min(dist(h, a_j), j = 1,2,...,sa)\} \quad (6)$$

The idea is that each member *a* from set A_t has a similar control function as a trop from endocrine paradigm.

Another specific issue of the proposed algorithm is the manner to select and recombine the hormones in order to generate descendants.

A special kind of *sharing* among the members of the current population H_t results. Due to the fact that each individual a_i from population A_t controls a class of hormones: $C(a_i)$, this individual of control, a_i, imprints to each hormone a probability of selecting it as first parent. The selection of first parent is made proportional to the value of its class, which is calculated according to formula:

$$val_i = \frac{1}{sizeof(C(a_i))} \quad (7).$$

First parent is selected from population H_t, proportionally with value of its class, so, we can affirm that the hormones from a particular class locally share the resources. By this manner of selecting first parent, the less crowded hormones are preferred and those zones from the search space, which are apparently disappearing, would be revived.

Let h_k be the selected first parent and a_i, its controller.

The second parent h_l, the mate of the parent h_k, is selected only from the

h_k 's class, $C(a_i)$. Parent h_l is proportionally selected with its performance, where performance value of a hormone *h* is given by the formula:

$$performance(h) = \frac{nr\_dominated}{sh} \quad (8)$$

and nr_*dominated* - represents the number of solutions from H_t, which are dominated by the hormone *h*.

By selecting the second parent proportionally with its performance, the method assures a faster convergence of the population toward Pareto front.

Crossover operator recombines two parents and produces a single descendant, which is accepted into the next population.

MENDA technique

1. ***Initialize_the_populations.***

   1.1. $t = 0$ (number of current generation);

   1.2. $sh = sa$. (initial size of the population A is the same with the size of the population H)

   1.3. Generate randomly the populations: $H_t = \{h_1, h_2, ..., h_{sh}\}$, population of hormones, and $A_t = \{a_1, a_2, ..., a_{sa}\}$, population of controllers, where: *sh* = size (H_t) and *sa* = size (A_t).

2. ***Repeat***

   2.1. ***Join the populations*** H_t ***and*** A_t***, resulting*** U_t. The population U_t contains all individuals from H_t and A_t. *sha* = size (U_t) = size (H_t)+size (A_t).

   2.2. ***Generate*** A_{t+1}. Population A_{t+1} embodies all non-dominated solution from U_t : $A_{t+1} = \bigcup \{u \in U_t, u\text{ - non - dominated}\}$, $sa = card(A_{t+1})$

   2.3. ***Classify the hormones from*** H_t ***according to*** A_{t+1} and set the crowding degrees for hormones. Each individual from A_{t+1} “control” the hormones from its neighborhood. Further, a particular hormone can recombine only with hormones from its class.

   2.4. ***Evaluate*** H_t. The performance of each hormone *h* is proportional with the number of other individuals of H_t, which are dominated by *h*.

2.5. ***Generate*** H_{t+1}**:**

$H_{t+1} = \Phi$ **;**

For each *h* from H_t, which is selected proportionally to its crowding degree do:

Select a mate *h'* from the class of *h* hormone.

Recombine *h and h'*, for creating the descendant *d*.

Include the descendant into the next generation: $H_{t+1} = H_{t+1} \cup \{d\}$

2.6. *t = t+1.*

Until (sa = sh).

Remarks: The algorithm ends when all individuals from H_t became non-dominated. Condition (*sa = sh*) could be replaced with another condition, as attaining a prefixed number of generations. Numerical experiments proved that for a population of size 100, the condition (*sa = sh*) is satisfactory for detecting an approximate Pareto front.

We also noticed that less crowded individuals or those individuals, which are distant from the set *A*, have a significant role for diversity preservation. So, the set *A* could also embody those individuals.

7. Numerical Experiments

Example 1.

We consider a minimization problem with two objectives of two variables. This test function was proposed by Lis and Eiben [11].

$$f_1(x_1, x_2) = \sqrt[8]{x_1^2 + x_2^2}$$

$$f_2(x_1, x_2) = \sqrt[4]{(x_1 - 0.5)^2 + (x_2 - 0.5)^2} \qquad \text{where, } x_1, x_2 \in [-5, 10].$$

Pareto front is discontinuous and concave, and next figures show the population at different generation, *t=2,3,4,5*. Population size is 80.

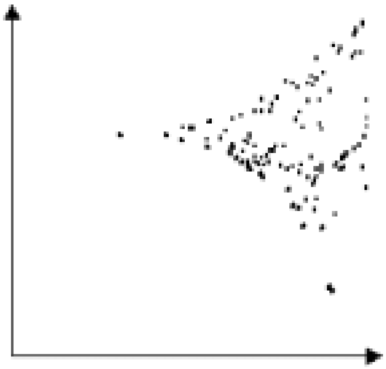

Figure 2: ***t=2***

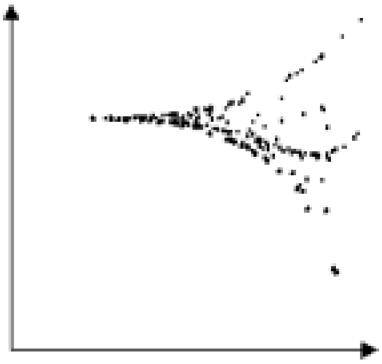

Figure 3: ***t=3***

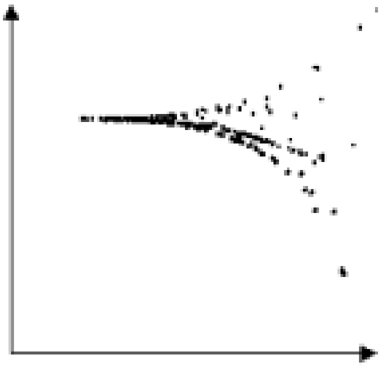

Figure 4: ***t=4***

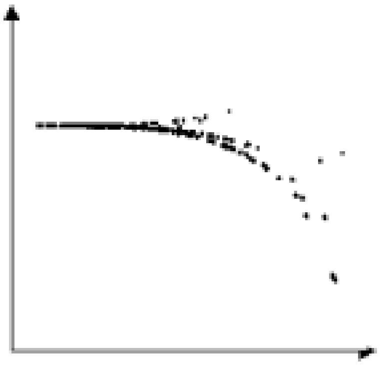

Figure 5: *t=5*

Example 2.

We consider next a test bi-objective function, with one variable, proposed by Schaffer [].

$$f_1(x) = \begin{cases} -x, & x \le 1 \\ -2 + x, & 1 < x \le 3 \\ 4 - x, & 3 < x \le 4 \\ -4 + x, & 4 < x \end{cases}, \quad f_2(x) = (x-5)^2, \text{ where, } x_1, x_2 \in [-5, 10].$$

Pareto front is discontinuous.

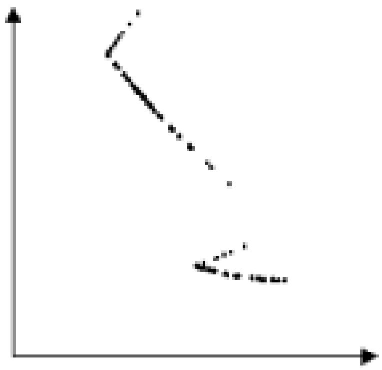

Figure 6: Pareto front, generation t=3

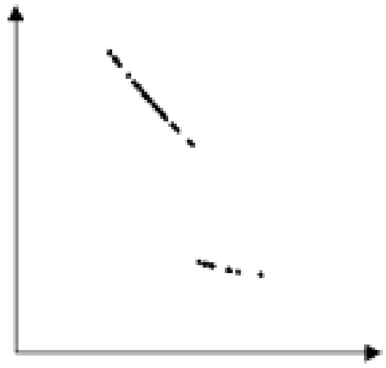

Figure 7: Pareto front, generation t=10

Example 3:

Our test functions also included a popular difficult test suit (*ZDT 1-6 bi-objective problems*), proposed by Zitzler, Deb and Thiele in [17]. *F* is a bi-objective function $F(\overline{x}) = (f_1(\overline{x}), f_2(\overline{x}))$ and the optimization problem is:

$$\begin{cases} \text{Minimize } F(x), \\ \text{subject to } f_2(x) = g(x_2,\ldots,x_m)h(f_1(x_1), g(x_2,\ldots x_m) \\ \text{where } \quad x = (x_1,\ldots,x_m) \end{cases}$$

For example:

ZDT1 problem:

$$f_1(\overline{x}) = x_1$$

$$g(x_2,\ldots,x_m) = 1 + 9\sum_{i=2}^{m}\frac{x_i}{m-1}$$

$$h(f_1, g) = 1 - \sqrt{\frac{f_1}{g}}$$

ZTD2 problem:

$$f_1(\overline{x}) = x_1$$

$$g(x_2,\ldots,x_m) = 1 + 9\sum_{i=2}^{m}\frac{x_i}{m-1}$$

$$h(f_1, g) = 1 - \left(\frac{f_1}{g}\right)^2$$

and *ZTD3 problem:*

$$f_1(\overline{x}) = x_1$$

$$g(x_2,\ldots,x_m) = 1 + 9\sum_{i=2}^{m}\frac{x_i}{m-1}$$

$$h(f_1, g) = 1 - \sqrt{\frac{f_1}{g}} - \frac{f_1}{g}\sin(10\pi f_1)$$

In all cases *m=30*, $x_i \in [0,1]$, and Pareto front is formed with *g(x)=1*.

A specific characteristic of those functions made the population to converge toward a segment of the Pareto front, a segment that corresponded with the lowest values of the first function. It can be noticed that if the first objective function depends only of one variable (for example: $f_1(\overline{x}) = x_1$), the second objective represents a function with *m-1* variables, where *m* is usually 30.

We observed that for *m=2*, the Pareto front is detected using our algorithm.

Intuitively, we assume that the proposed evolutionary algorithm minimizes the values of the first function more quickly than the values of the second one. Thus, the final solutions correspond to a small part of the Pareto front, where the first objective's values are lower.

Due to this fact, a modification must be made in order to obtain the entire Pareto front. Our proposal is to change the variation operator, respectively the crossover operator.

The standard crossover operator is applied on two selected parents $x = (x_1, x_2, ..., x_m)$ and $y = (y_1, y_2, ..., y_m)$, resulting the unique descendant $z = (z_1, z_2, ..., z_m)$, where: $z_i = (1-q) \cdot x_i + q \cdot y_i$ and *q* – randomly generated.

The modified operator generates the unique descendant $z = (z_1, z_2, ..., z_m)$, too. Considering λ from *[0,1]* (usually 0.5), representing a parameter of the algorithm, the modified crossover operator performs as follows:

Modified Crossover Operator

For each *i* from *2* to *m*
    $z_i = (1-q) \cdot x_i + q \cdot y_i$
endFor
Randomly generate *p* from *[0,1]*.
If *p*> λ then
    $z_1 = (1-q) \cdot x_1 + q \cdot y_1$
else
    randomly generate a value for z_1 from the specific domain.
endIf.

This alteration of crossover operator gives good results. The algorithm works with a population of size 100. The algorithm ends when the population contains only non-dominated solutions.

The next figures show the final Pareto Front for *ZDT1,2 and 3* problems.

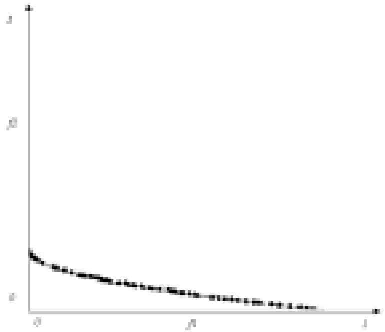

Figure 8 ZDT3, Pareto front after 15 generations

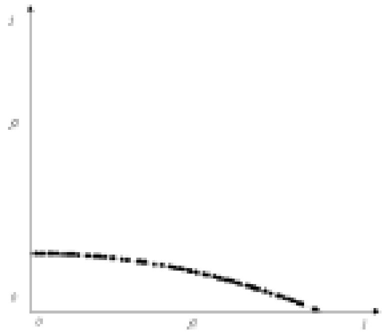

Figure 9 ZDT2, Pareto front after 15 generations

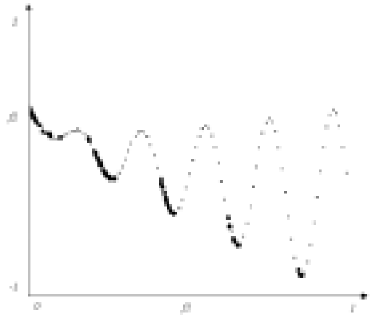

Figure 10: ZDT3, Pareto front after 10 generations

8. Conclusions

Nature offers complex phenomenon, processes and systems, which can inspire us in many ways. An example of this kind is the natural endocrine system. It reveals us as a dynamic, adaptive and semi-independent system. Its complex structural and functional features suggest us a possible imitation of its characteristics for developing new techniques for multiobjective optimization.

It is clearly that hormonal system was ignored by now. Our work essentially attempts to mimic hormones' behavior in order to solve difficult problems like multiobjective optimization. Consequently, we propose a new technique based on endocrine paradigm, called *MENDA*. It provides satisfactory solutions in our tests.

Further directions could be improving the proposed algorithm and more tests with different multiobjective function.

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