Genetic Algorithm Based Feature Ranking in Multi-criteria Optimization

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Summary
Evolutionary algorithms such as Genetic Algorithms (GAs) have become the method of choice for optimization problems that are too complex due to their advantages compared to other methods. GAs require little knowledge about the problem being solved, and they are easy to implement, robust, and inherently parallel. GAs often take less time to find the optimal solution than other methods. However, most real-world problems involve simultaneous optimization of several often mutually concurrent objectives. GAs are able to find optimal solutions in an overall sense. This paper deals with a special case of multi-objective optimization problems from the medical domain which are of a very high practical relevance. One of the problems is to rank the treatments for Trigeminal Neuralgia. The second problem is to rank the risk factors for Bronchial Asthma. We use a simple multiple objective procedure and an evolutionary scheme for solving the problems. Results obtained by the proposed approach in a very simple way are same as the results (or even better) obtained by applying weighted-sum method. The advantage of the proposed technique is that it does not require any additional information about the problem.

Keywords:
Multi-Criteria Optimization, Feature Ranking, Genetic Algorithm, Trigeminal Neuralgia, Bronchial Asthma.

1. Introduction

In a multi-objective optimization problem, instead of one scalar objective function, usually several conflicting criteria appear in an optimization problem. Multi-objective optimization is also known as multi-criteria, Pareto, vector optimization where a set of Pareto optima exists as solution. In practical applications, however, the designer wants only one optimal solution and it is required to introduce some preferences in order to find the best solution among Pareto optima. One popular approach is to combine all the criteria into one scalar objective function. Another approach is to choose one of the criteria as the objective function and transform the others into constraints. These techniques may look reasonable but they prove to have several shortcomings. A Pareto optimal set is regarded as the mathematical solution to a multi-objective problem. There are some particular situations for which Pareto dominance cannot be applied while considering the problem as multi-objective without reducing it to a single objective one. For instance, in the situation where all solutions are non-dominated, we cannot say that one is better that the other by simply applying Pareto dominance definition. In this paper, two multi-objective optimization problems are analyzed from the medical domain for which Pareto dominance alone cannot decide which solution is the best.

(1) ranking a set of Treatments applied for Trigeminal Neuralgia by taking into account several criteria. As evident from the considered test data, Pareto dominance cannot be applied in its initial form for classifying these treatments. The result will be that all solutions are non-dominated (i.e., all are equal).
(2) ranking a set of risk factors for Bronchial Asthma by taking into account multiple criteria. In this case also, Pareto dominance alone cannot decide which hierarchy is the best (most of the solutions are non-dominated between them).

The data for both problems were obtained from [1]. An evolutionary scheme is applied for ranking these treatments. A dominance concept between two solutions is used. Results obtained are compared with the results obtained by weighted-sum method. The paper is structured as follows: Section 2 provides details about both problems studied; Trigeminal Neuralgia and Bronchial Asthma. Section 3 describes the effective problem we have to solve in both situations. Section 4 gives general information about Genetic Algorithms. Section 5 introduces and explains the proposed approach. Section 6 presents the weighted-sum method used for comparing the results of the proposed approach. Section 7 is dedicated to the experiment. Section 8 contains discussions and conclusions of the paper, Tables, Figures and Equations.

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2. Medical Problems Considered

2.1. Case study I—Trigeminal Neuralgia

Trigeminal neuralgia is a condition that affects the trigeminal nerve; one of the largest nerves in the head. The trigeminal nerve is responsible for sending impulses of touch, pain, pressure, and temperature to the brain from the face, jaw, gums, forehead, and around the eyes. Trigeminal neuralgia is characterized by a sudden, severe, electric shock-like or stabbing pain typically felt on one side of the jaw or cheek. The disorder is more common in women than in men and rarely affects anyone younger than 50 years. The attacks of pain, which generally last several seconds and may be repeated one after the other, may be triggered by talking, brushing teeth, touching the face, chewing, or swallowing. Trigeminal neuralgia most frequently affects women older than 50 years. Such cases are usually linked to damage from diseases of central nervous system. Medications for trigeminal neuralgia typically include anticonvulsant such as carbamazepine or phenytoin. Baclofen, clonazepam, gabapentin, and valproic acid may also be effective and may be used in combination to achieve pain relief.

2.2. Case study II—Bronchial Asthma

Asthma (Bronchial Asthma) is an inflammatory disorder of the airways, characterized by periodic attacks of wheezing, shortness of breath, chest tightness, and coughing. When an asthma attack occurs, the muscles of the Bronchial tree become tight and the lining of the air passages swells, reducing airflow and producing the characteristic wheezing sound. Mucus production is increased. Bronchial Asthma is a public health problem with gradually increasing importance, affecting more than 100 million individuals worldwide and found independently of the level of development of the country. Most people with asthma have periodic wheezing attacks separated by symptom-free periods. Some asthmatics have chronic shortness of breath with episodes of increased shortness of breath. Other asthmatics may have cough as their predominant symptom. Asthma symptoms can be triggered by inhaled allergens such as pet dander, dust mites, cockroach allergens, molds, or pollens. Asthma symptoms can also be triggered by respiratory infections, exercise, cold air, tobacco smoke and other pollutants, stress, food, or drug allergies. Asthma is found in 3–5% of adults and 7–10% of children. Recognizing the risk factors is important for the diagnosis and prevention of the disease.

3. Problem Formulation

3.1. Trigeminal Neuralgia Treatment Ranking

For the treatment of Trigeminal Neuralgia, many methods can be applied. The chronic evolution of the disease and the variable response to different treatment methods creates many disputes in the scientific world. The evaluation of the treatment methods from multiple points of view is difficult and has a high degree of subjectivity. The problem is to rank treatments illustrated in Table 1 subject to multiple criteria listed in Table 2. The evaluation matrix case is presented in Table 3.

Table 1
Treatments applied for Trigeminal Neuralgia

Treatment	
T1	Infiltrations with streptomycin
T2	Low level laser therapy
T3	Treatment by skin graft
T4	Treatment by sciatic nerve graft
T5	Treatment by neurectomy

Table 2
Criteria considered for treatment efficiency evaluation

Criterion	
C1	Hospitalization period
C2	Remission period
C3	Pain relief
C4	Decrease in the number of crises
C5	Decrease in pain level
C6	Decrease of the pain area
C7	Decrease in medication

3.2. Bronchial Asthma Risk Factors Ranking

Bronchial Asthma occurs following the interaction between genes and environment, but none of these factors are enough for the disease to express itself. The goal is to establish a hierarchy of the risk factors for BA and the onset of asthma in phenotype. Patients are usually exposed to risk factors which can be grouped into two categories such as: genetic factors and environmental factors which are listed in Table 4. Also, the values of all criteria for the considered risk factor averaged for all the studied patients are given in Table 4. All objectives are to be maximized. It is evident that most of the risk factors are non-dominated between them. Only few risk factors are dominated (for instance risk factors 9, 10, 12 and 15). Asthma onset coefficient (denoted by CDA) represents an estimate of the risk regarding the BA onset in phenotype which is calculated as the average age of the BA onset in patients exposed to a certain (risk) factor (denoted by VDR) and the average age of the BA onset in patients non-exposed to the corresponding (risk) factor (denoted by VDF). Asthma onset coefficient CDA has values between -1 and 1.

Table 3.The Evaluation Matrix

Criteria	Criterion type	Treatment				
		Infiltrations with streptomycin T1	Low level Laser Therapy T2	Treatment by skin graft T3	Treatment by sciatic nerve graft T4	Treatment by neurectomy T5
Hospitalization Period, C1	Min	12.143	13.625	15.093	15.417	16.778
Remission Period, C2	Min	9.964	10.453	12.07	11.889	12.022
Pain Relief, C3	Max	21	18.34	25.2	34.742	18.457
Number of Crises, C4	Max	6.667	6.688	11.209	9.75	7.244
Pain level, C5	Max	3.423	3.281	3.558	3.833	3.156
Pain area, C6	Max	0.904	0.937	0.937	0.978	0.848
Medication, C7	Max	364.286	442.188	655.814	586.111	255.556

Table 4. The Values of the considered risk factors for the Bronchial Asthma with respect to the considered criteria.

S.No	Risk Factors	Criteria					
		BA	Conjunctivitis	Rhinitis	Urticaria	Eczema	CDA
1.	House dust mite	81.3	0	21.9	25	12.5	0.218448
2.	Father's BA	84.6	23.1	15.4	15.4	15.4	0.144254
3.	Eczema to antecessors	80	40	40	20	0	-0.22581
4.	Smoking mother	80.6	6.5	9.7	19.4	6.5	0.214712
5.	Traffic Pollution	80	3.2	9.7	9.7	12.9	0.338986
6.	House Environment(crowd)	73.9	5.8	15.9	23.2	10.1	0.231362
7.	Smoking of other members of the family	71.7	7.5	11.3	17	7.5	0.228511
8.	Industrial pollution	64	8	24	28	8	0.148545
9.	Mother's BA	77.3	0	4.5	9.1	0	0.169509
10.	BA to antecessors	66.7	2.4	12.2	22	6.1	0.087415
11.	Life in the city	65.6	6	15.8	22.6	7.5	0.02771
12.	Maternal transmission of BA and atopies	67.3	0	12.7	16.4	7.3	-0.01284
13.	Rhinitis to antecessors	65	6.7	18.3	15	8.3	-0.19996
14.	All allergies to antecessors(without BA)	60.4	4.4	16.5	17.6	5.5	-0.16459
15.	Urticaria to antecessors	53.2	3.2	11.3	21	3.2	-0.19033

4. Introduction to Genetic Algorithm

Genetic Algorithms (GAs) are a family of computational models inspired by evolution. Genetic Algorithms (GAs) have been successfully applied to solve search and optimization problems. The basic idea of a GA is to search a hypothesis space to find the best hypothesis. A pool of initial hypotheses called a population is randomly generated and each hypothesis is evaluated with a fitness function. Hypotheses with greater fitness have higher probability of being chosen to create the next generation. Some fraction of the best hypotheses may be retrained into the next generation, the rest undergo genetic operations such as crossover and mutation to generate new hypotheses. This process is iterated until either a predefined fitness criterion is met or the preset maximum number of generations is reached. A GA generally has four components. 1) A population of individuals where each individual in the population represents a possible solution. 2) A fitness function which is an evaluation function by which we can verify whether an individual is a good solution or not. 3) A selection function which decides how to pick good individuals from the current population for creating the population for the next generation. 4) Genetic operators such as crossover and mutation which explore new regions of search space while retaining some of the current information (individual) which is more important and ought to be present in the next generation which is termed as "survival of the fittest".

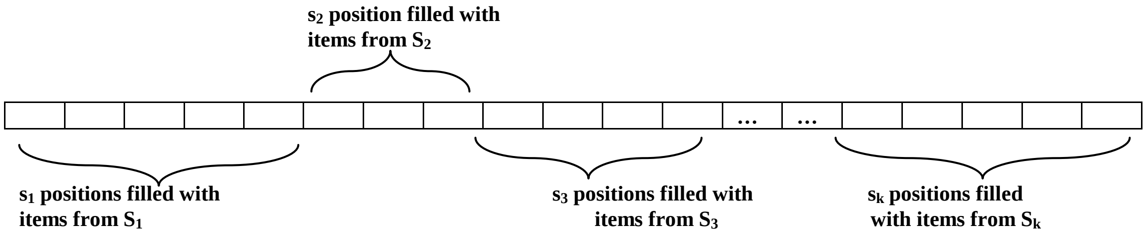

Fig 1. Example of a Chromosome having *k* levels of dominance.

	T1	T2	T3	T4	T5
T1	**X**	**4**	**2**	**2**	**6**
T2	**3**	**X**	**2**	**2**	**5**
T3	**5**	**5**	**X**	**3**	**7**
T4	**5**	**5**	**4**	**X**	**7**
T5	**1**	**2**	**0**	**0**	**X**

Fitness(C) = 2

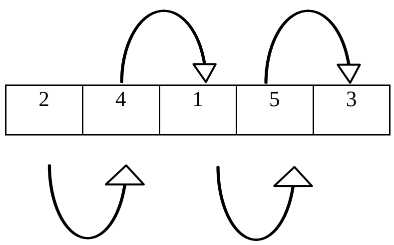

Fig 2. Example of fitness function calculation

The following is a typical GA procedure:

```
Procedure GA
Begin
        Initialize population;
        Evaluate population members;
        While termination condition not satisfied do
Begin
        Select parents from current population;
        Apply genetic operators to selected parents;
        Evaluate offspring;
        Set offspring equal to current population;
End
End
```

4.1. Feature Ranking and Subset Selection

The term feature subset selection is applied to the task of selecting those features that are most useful to a particular classification problem from all those available. The main purpose of feature subset selection is to reduce the number of features used in classification while maintaining acceptable classification accuracy. The selection of features can have a considerable impact on the effectiveness of the resulting classification algorithm. Feature ranking is a process where the relative importance of each feature is computed so that feature selection task becomes easier.

5. Proposed evolutionary algorithm approach

Evolutionary Algorithm (EA) is applied for ranking the features. A special encoding technique is used to initialize the population based on some existing information about the features that must be ranked (treatments for Trigeminal Neuralgia and risk factors for Bronchial Asthma, respectively). The evolutionary scheme used here is divided into several steps as presented below.

5.1. Population initialization

For initializing the population in a way which will help in finding the final solution individuals are generated randomly. Each chromosome is represented as a string whose length is equal to the number of units which must be ranked (for instance, treatments in the case of Trigeminal Neuralgia and risk factors for Bronchial Asthma). Instead of filling the positions in the chromosomes with random generated values between 1 and the number of units, a procedure is followed as described below:

1. Using Pareto dominance, all the non-dominated units (treatments and risk factors, respectively) are kept in a separate set (and not considered in the initial set anymore). Let us denote this set by S1 and the size of this set by s1. Therefore, the first s1 positions in the chromosome consist of a permutation of the units (indices) from the set S1 whose order is randomly generated.
2. The procedure described above is repeated until all the levels of non-dominated units are selected.

This means, from the remaining units, the non dominated solutions are again selected. These units are non-dominated only in respect to the current content of the units set. This newly obtained set is denoted by S2 and its size is denoted by s2. The minimum number of such levels can be 1 (which means all the solutions are non-dominated) and can be maximum the size of the units set. All the units, which were previously removed from the initial set, will dominate these units. Consequently, chromosome positions between s1+1 and s2 will consist of random permutations of the units (indices) which are dominated by a single other unit (and are the units belonging to the set S2), positions between s2+1 and s3 will consist of permutations of the units which are dominated by 2 units (the units from the set S3, and so on. A graphical example of a chromosome is depicted in Fig. 1. A chromosome is composed of as many segments as the number of levels of dominance, each segment having a different number of genes.

5.2. Fitness function

From the initialization of a chromosome, it is obvious that one gene (which represents an item in our examples, i.e. a treatment in the first case and a risk factor in the second case) cannot be dominated by a successive gene. Two consecutive genes can represent either non-dominated items or the second one is dominated by the first one. For establishing a hierarchy when all the items are non-dominated and from a multi-objective perspective, the fitness of a chromosome is computed as described in Algorithm1.

Algorithm 1. Fitness function calculation

Set the value of the fitness function to 0.

For each pair of genes (i, i+1) the number of objectives for which i is better than i+1 is calculated

If this number is less than $\frac{\text{number of objectives}}{2}$

(in this case the number of objectives is an even number) or it is less than integer portion of

$\frac{\text{number of objectives}}{2} + 1$

(in this case the number of objectives is an odd number) then the value of objective function is increased by 1.

The fitness function will reflect the number of items (treatments, risk factors) which are not correctly arranged with respect to the number of objectives in which one is better than the other As depicted in Fig. 1

We consider as example the first case studied in this paper: the Trigeminal Neuralgia treatments. We consider there a chromosome whose genes are (2, 4, 1, 5, 3), which represents the order in which treatments are arranged. Let us use this chromosome as an example and show how the fitness will be calculated in this case.

As evident from the table presented in Fig. 2, treatment 2 is better than treatment 4 with respect with two objectives (out of seven). Which means, order must be (4, 2) and not (2, 4). Therefore, the fitness value will increase by 1. Treatment4 is better than treatment 1 for five of the seven objectives. This means that the order (4, 1) is correct. Treatment 1 is better than treatment 5 for six of the objectives. Again, the pair (5, 1) is correctly arranged.

Treatment 5 is not better than treatment 3 for any of the objectives. Means, the order (5, 3) is not correct and fitness will again increase by one. Finally the value of fitness function is equal to 2. Our objective is to obtain the value 0 for the fitness function.

5.3. Evolutionary algorithm

Algorithm 2. The pseudo code of the proposed evolutionary scheme

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Step 1. **Initialize population** following the rules described in the population Initialization section.

Repeat

Step 2. **Compute** the **fitness** (quality) of all individuals

Step 3. Perform **self crossover** on each solution from the population.

```
if fitness (parent) <fitness (offspring)
        keep the parent for the next generation
else if
        keep the offspring for the next generation
else
        pick at random between parent and
        offspring for the next generation.
```

Until a given number of generations is reached.

Step 4. Print all the individuals with fitness 0.

The evolutionary scheme adopted here is very simple and uses only crossover as genetic operator. This operator, called the Self-crossover, acts as both crossover as well as mutation operator. The self-crossover operator works in the following way:

Each individual in the current solution is affected by self-crossover operation. Then the parent and offspring are directly compared. The one with a smaller fitness will be kept into the population of the new generation. The pseudo code of the proposed approach is briefly presented in Algorithm 2.

5.4. Self-crossover (SC)

Unlike conventional crossover mechanism, self crossover mechanism alters the genetic information within a single potential string selected randomly from the mating pool to produce an offspring. This is done in such a manner that the stochastic and evolutionary characteristics of GAs are preserved.

Let S=
be a string of length 10 selected from the mating pool. For self-crossover, first we select a random position p (0<p<L) and generate two substrings s_1 and s_2; where s_1 = bits 1 through p of S and s_2 = bits p+1 through L of S. Now we select two random positions p_1, 0 <= p_1 <= p and p_2, 0<= p_2 <= (L-p). Then four substrings are generated as follows:

s_{11} = bits 1 through p – p1 of s_1.
s_{12} = bits (p - p_1 + 1) through p of s_1.
s_{21} = bits 1 through (L – p – p2)of s_2.
s_{22} = bits (L - p2 + 1) through L of s_2.

Using operations similar to crossover we generate $S^1 = s_{11} \mid s_{22}$ and $S^2 = s_{21} \mid s_{12}$. Finally, the self- crossovered offspring of S is generated as $S_1 = S^1 \mid S^2$. It is easy to see that number of 1's in S and S_1 is the same. We now explain it with the example string S of length 10.

8	7	4	5	6	2	1	10	3	9

S=

A random position, p=4 is selected for splitting the string into two substrings (s_1, s_2) as follows:
s1 = 8 7 4 5
s2 = 6 2 1 10 3 9

Now two random positions p_1 = 1 and p_2 = 4, are selected for s_1 and s_2 respectively. After splitting s_1 and s_2 at 1st and 4th positions respectively, we get,
s_{11} = 8 7 4
s_{12} = 5
s_{21} = 6 2
s_{22} = 1 10 3 9

The two new substrings S^1 and S^2 are then obtained as:
S^1 = 8 7 4 1 10 3 9
S^2 = 6 2 5

Finally, the offspring S_1 is generated by concatenating S^1 and S^2 as:

S_1 = 8 7 4 1 10 3 9 6 2 5
Thus, self-crossover exchanges substrings s_{12} and s_{22}. No parent string will have repeated numbers in this problem. Also no offspring will have repeated values since the values are not changed; only their positions are changed. So, self-crossover will evolve new offsprings as iterations go on.
We can see very well that mutation is not effective in producing such constrained offsprings. But self-crossover can regenerate any lost genetic information. So we may not need mutation when we use the new technique in constrained GA Application.

8	7	4	5	6	2	1	10	3	9

6. Weighted-sum approach

The weighted-sum method is a simple, popular method that changes the weights among objective functions to obtain the Pareto front. Let us consider we have the objective functions f_1; f_2; . . . ; f_n. This method takes each objective function and multiplies it by a fraction of one, the ''weight'' which is represented by w_i. The modified functions are then added together to obtain a single cost function, which can easily be solved using any single objective optimization method. Mathematically, the function is written as:

$$\sum_{i=1}^{n} wifi \text{ , where } 0 \le w_i \le 1 \text{ and } \sum_{i=1}^{n} wi = 1 \qquad (1)$$

The weight itself reflects the relative importance among the objective functions under consideration.

There are several disadvantages of this technique:

- the user always has to specify the weights values for functions and sometimes this may not have any relevance to the importance of objectives;
- A single solution is obtained at a time. If we are interested in obtaining a set of feasible solutions, the algorithm has to be run several times. Also, there is no warranty that the solutions obtained in different runs are different.

7. Experiment results and discussions

The proposed approach is applied for ranking the treatments for Trigeminal Neuralgia and the risk factors for Bronchial Asthma. Results obtained by the proposed approach are compared with the results obtained by weighted-sum approach .

7.1. The case of trigeminal neuralgia

7.1.1. Proposed approach evaluation

The parameters used by the evolutionary approach for the Trigeminal Neuralgia case study are:

- Population size: 8.
- Number of generations: 10.

The hierarchy of treatments efficiency obtained is:

T4; T3; T1; T2; T5.

An evolution of the fitness function can be analyzed in Fig. 3. The minimum, maximum and average fitness values are depicted for each iteration.

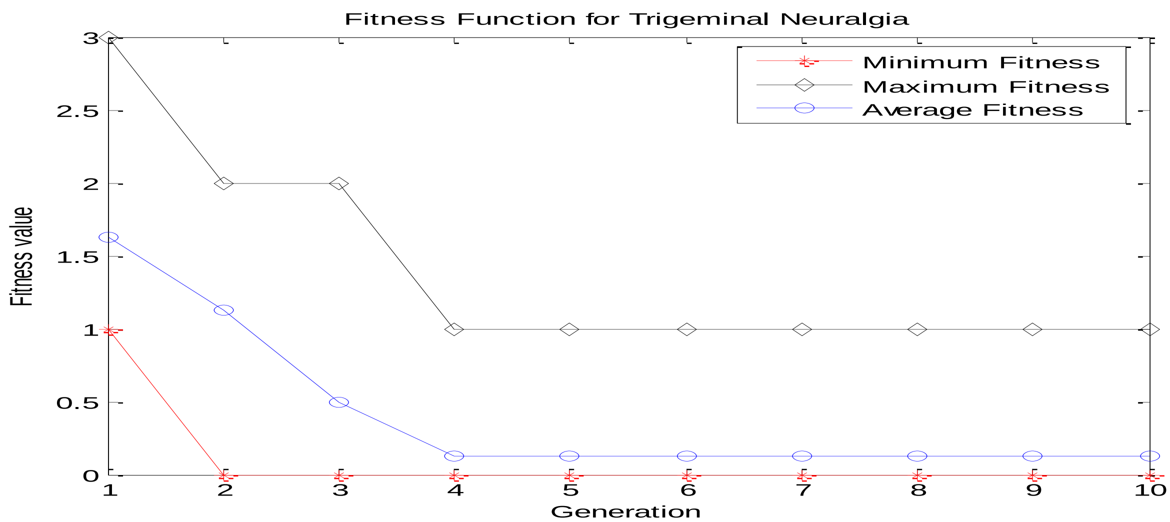

Fig.3. Evolution of the fitness function for the Trigeminal Neuralgia case study : Minimum , Maximum, average fitness.

7.1.2. Weighted-sum approach evaluation

As evident from Table 3, first two objectives have to be minimized and last 5 objectives have to be maximized. Weighted-sum approach considers all objectives as having same optimization type (minimization or maximization). For this purpose we consider -f1 and -f2 instead of f1 and f2.This way all objectives have to be maximized. In order to apply weighted-sum method, a weight has to be specified for each criterion. For the seven studied criteria we established specific values within the interval 0.02–0.54. For the hospitalization period and for the remission period, the values were more relevant as they decreased. For the other evaluated parameters, higher values expressed a good efficiency of the evaluated treatment method. Empirical results obtained by applying weighted-sum approach are presented in Table 5. As evident from Table 5, the ranking of the above treatments in decreasing order of its efficiency obtained by applying weighted-sum approach is: T4 (Sciatic nerve graft), T3 (Skin graft), T1 (Streptomycin), T2 (Laser) and T5 (Neurectomy).

7.2. The case of Bronchial Asthma

7.2.1. Proposed approach evaluation

The parameters used by the evolutionary approach for the Bronchial Asthma case study are:

- Population size: 25.
- Number of generations: 25.

Several hierarchies of risk factors are obtained. All the solutions are non-dominated between them. Some of the solutions obtained in the final generation are presented in Table 6. The evolution of the fitness function (performance measure) can be analyzed using Fig. 4.

The minimum, maximum and average fitness values are depicted for each iteration.

7.2.2. Weighted-sum approach evaluation

The weight of each criterion has been evaluated following its frequency in the patient phenotype. The frequencies of the allergies of the patient have been mentioned. BA was evaluated with the frequency of the patients with BA alone. The sum of frequencies is 114, 3% which represents 100 points from the total weight. Thus, has been set the weight of each criterion. BA and BA onset have been initially evaluated together, with a total weight of 58 points, and then they have been evaluated after the importance considered to represents the BA onset in the evaluation of the risk disease and have been granted 8 points. Results obtained by applying weighted-sum method are presented in Table 7.

7.2.3. Results analysis

As evident from the first experiment, both algorithms obtained same hierarchy for the treatments. The advantage of the evolutionary approach is more evident for the second case study which was more difficult. Some important aspects of the proposed evolutionary approach are depicted below:

(1) Several alternative solutions are obtained by the evolutionary approach when compared to a single solution obtained by the weighted-sum approach. Of course, by selecting different values for the weights, multiple solutions can be obtained by the weighted-sum method also, but in different runs. But in this case, weights are important. For instance, a weight whose value was 0.5 (out of 1) or 50 cannot be 0.1. This means there is no rule in establishing the importance of objectives. So choosing the appropriate weights is not an easy task.

Table 5. Results obtained by applying weighted-sum approach.

Treatment	Criteria							Weighted-sum
	C1	C2	C3	C4	C5	C6	C7	
T1	12.143	9.964	21.0	6.667	3.423	0.904	364.286	18.21691
T2	13.635	10.453	18.34	6.688	3.281	0.922	442.188	18.16829
T3	15.093	12.07	25.2	11.209	3.558	0.937	655.814	26.34107
T4	15.417	11.889	34.742	9.75	3.833	0.978	586.111	30.01671
T5	16.778	12.022	18.457	7.244	3.156	0.848	255.556	14.17278
Weights	0.08	0.06	0.54	0.08	0.17	0.05	0.02	

Table 6. Example of non-dominated solutions obtained by the Evolutionary approach for the Bronchial Asthma case study.

1.	2	11	4	3	8	1	7	5	6	13	14	12	10	15	9
2.	8	7	14	5	6	2	1	11	3	13	4	10	12	15	9
3.	2	1	7	11	13	4	3	5	6	8	14	12	10	15	9
4.	1	8	3	2	7	14	5	6	4	13	11	12	10	15	9
5.	7	13	4	14	5	1	8	6	2	11	3	12	10	15	9
6.	8	1	4	3	2	5	6	7	13	11	14	12	10	15	9
7.	14	5	1	2	8	6	11	3	7	13	4	12	10	15	9
8.	1	6	8	13	11	5	7	4	3	2	14	12	10	15	9
9.	1	2	6	7	13	14	5	8	3	11	4	10	12	15	9
10.	3	6	2	1	8	13	14	5	7	11	4	10	12	15	9
11.	1	7	14	5	6	4	3	2	8	11	13	10	12	15	9
12.	1	8	6	2	14	5	13	4	3	7	11	12	10	15	9
13.	6	13	14	5	8	1	2	7	4	11	3	10	12	15	9
14.	1	6	2	14	5	7	13	4	3	8	11	10	12	15	9

For instance, we considered decreasing of pain criteria as being a very important one (weight is 0.54) and medication period (or hospitalization period) as having a less importance (weights are 0.08 and 0.02, respectively). If the pain weight and medication weight are exchanged we cannot have any warranty of the result quality.

(2) As evident from the data given in Table 7, the risk factor 9 is dominated with respect to all objectives by three other risk factors (1, 4 and 5), risk factor 15 is dominated by two risk factors (6 and 8), and risk factors 10 and 12 are dominated by a single risk factor (6). This means, in the resulting hierarchy, factor 9 must be on the last position. Factors 15, 10 and 12 are also dominated and must be in one of the last positions. But this is not evident from the hierarchy obtained by the weighted-sum approach. All these domination relations are taken into account by the evolutionary method and several alternatives of risk factors ranking are obtained at the end of the search process. In the results obtained by the evolutionary approach for the second case study, genetic factors are of a very high importance. Also, hierarchy obtained by the evolutionary approach shows the same results as weighted sum method. Experiment results show a very fast convergence of the evolutionary approach. The evolutionary approach proposed herein is very flexible and can be applied to any problem of this kind. No additional information about the problem is required as in case of weighted sum method.

8. Discussions and conclusions

Choosing of the treatment in the case of Trigeminal Neuralgia is a difficult task since the patients have different responses in time to the same treatment method. Also a treatment method does not have constant better effects on all criteria than another. This practically means that Pareto dominance will not provide any information about the dominance of one treatment or another. All are classified as equal. By applying evolutionary algorithms, the ranking of treatments can be obtained without requiring any additional information as opposed to the weighted sum approach, which requires a weight for each objective. This task can be sometimes difficult to achieve due to the ambiguity in the importance of objectives. By combining all objectives into a single objective function, we can obtain at most one solution. In order to obtain multiple solutions we have to apply the algorithm several times. Even then, we cannot be sure that all solutions are different. Running time required is another disadvantage of the weighted-sum approach. This is the case for our second case study: Ranking the Risk Factors for

Bronchial Asthma. The evolutionary approach obtains several solutions in one run. Also, the dominance concept plays an important role in the final hierarchy. Both genetic and environmental factors increase the risk for the Bronchial Asthma and their influence differs from a patient to another, from a world region to another, etc. That's why a right classification of the risk factors is very important in control and prevention of Bronchial Asthma.

Table 7. Results obtained by weighted-sum method for the Bronchial Asthma case study.

Risk factor	Criteria						Score
	BA	Conjunctivitis	Rhinitis	Urticaria	Eczema	CDA	
House dust mite	81.3	0	21.9	25	12.5	0.22	50.74
Father's BA	84.6	23.1	15.4	15.4	15.4	0.14	50.23
Eczema to antecessors	80	40	40	20	0	-0.2	48.79
Smoking mother	80.6	6.5	9.7	19.4	6.5	0.21	47.61
Traffic Pollution	80	3.2	9.7	9.7	12.9	0.34	46.71
House Environment(crowd)	73.9	5.8	15.9	23.2	10.1	0.23	46.11
Smoking of other members of the family	71.7	7.5	11.3	17	7.5	0.23	43.12
Industrial pollution	64	8	24	28	8	0.15	42.42
Mother's BA	77.3	0	4.5	9.1	0	0.17	42.32
BA to antecessors	66.7	2.4	12.2	22	6.1	0.09	40.27
Life in the city	65.6	6	15.8	22.6	7.5	0.03	40.05
Maternal transmission of BA/atopy	67.3	0	12.7	16.4	7.3	-0.01	38.75
Rhinitis to antecessors	65	6.7	18.3	15	8.3	-0.2	36.89
All allergies to antecessors(without BA)	60.4	4.4	16.5	17.6	5.5	-0.2	34.87
Urticaria to antecessors	53.2	3.2	11.3	21	3.2	-0.2	30.85
Weights	**50**	**4**	**13**	**19**	**6**	**8**	

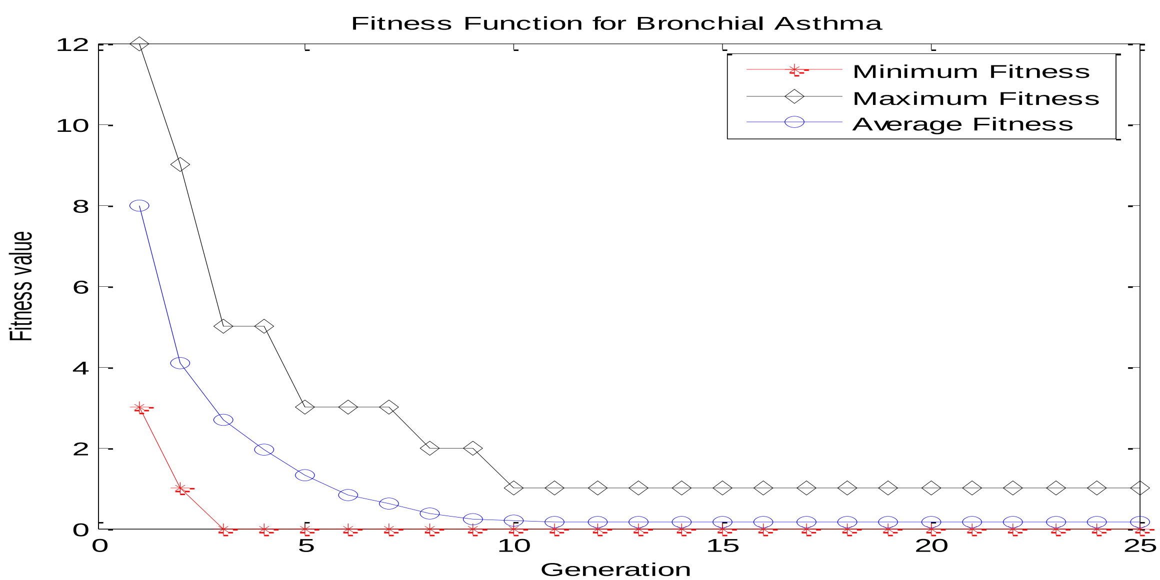

Fig.4. Evolution of the fitness function for the Bronchial Asthma case study : Minimum, maximum and average values.

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