Pareto-directed Interactive Concept-based Evolution

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Abstract **– In this paper we expand our concept-based evolution method, which facilitates team's brainstorming for conceptual design, to be guided by an interactive Pareto-directed approach. The survivability of conceptual solutions is influenced by both model-based fitness and teammates' perceptions and preferences. The suggested method produces an objective-subjective front. Academic examples are employed to demonstrate the proposed approach.**

I. INTRODUCTION

Most research work on the use of Multi Objective Evolutionary Algorithms (MOEA) for engineering design does not deal with conceptual design. Recently, we have introduced a concept-based evolutionary method, which strengthens symbiosis between computers and humans in exploring engineering solutions to multi-objective design problems [1, 2]. The use of concepts improves the human-machine interface. It serves not only as a communication means but also enables evaluating concepts, rather then just specific solutions, while taking into account teammates' perceptions and preferences.

In our previous publications [1,2], we have used a progressive goal approach, rather than the common use of a Pareto front approach. This was motivated by Branke et al. [3], who provided a discussion on the use of Pareto-based methods in real-world design problems, and pointed at some deficiencies. We further argued, with respect to our application, that the class of non-dominated solutions is useful in checking optimality relations among individual solutions, but do not lend itself easily to searching and evaluating engineering concepts. This is because the front is an optimality-based comparison rather than a concept-based one.

Here we re-examine our conviction and manage to develop a new method. It enables the evaluation of design concepts using an interactive evolution, which is guided by a Pareto-directed approach. In comparison with the dynamic target approach used in [2], the current methodology allows a non-localized inspection of the design space with respect to the objective space.

Pareto-based approaches are between the most popular MOEA solution techniques [4]. Surveys and descriptions of such algorithms can be found in several references (e.g., [4-6]). Many MOEAs use non-dominancy ranking to maintain search pressure, as well as fitness sharing to ensure diversity in the front's population (e.g., MOGA [7], NPGA [8], NSGA, [6]). Other MOEAs use elitism (e.g., SPEA [9], NSGA II [6]).

It is noted that Pareto fronts of several design concepts have been recently used to assess conceptual design solutions in multi-objective search spaces. Anderson, [10], used genetic algorithms to separately produce the Pareto fronts of several concepts. These fronts were introduced on the same graph for further evaluations by the designers. Mattson, [11], used a non-evolutionary method to also produce separate Pareto fronts of concepts, and then combined them to a mutual front by the s-Pareto approach.

Cvetkovic, [12], developed an agent-based MOEA system, which supports conceptual design through designers' preferences. Cvetkovic introduced scenarios, which allow constraints' articulation involving design parameters and objectives. Parmee, [13], examined concepts using a structured genetic algorithm, (StGA), which facilitates a hierarchical approach. As indicated by Parmee, StGA, by itself, does not overcome the problem of the lack of diversity in search direction within a highly discontinuous design space.

Interactive EC-based (IEC) systems are sometimes termed collaborative evolutionary systems, indicating collaboration between humans and computers. A recent extensive review on IEC, by Takagi [14], shows that the majority of efforts are divided into application-driven research, and to efforts at reducing the fatigue of intensive human evaluation of the designs. In design, two possible types of human intervention with respect to the selection process should be pointed out. The first is based on the availability of some computational model that provides calculated objectives, and the intervention is commonly restricted to weighting of objectives by the designers. In the second type, which is common in fashion design, the designers provide directly the fitness for the individual solutions.

In this paper, a novel Pareto-directed interactive concept-based evolutionary approach is suggested, in which human interventions are primarily related to concepts and sub-concepts. The survivability of a concept in the proposed evolutionary algorithm, depends on both the calculated performance and human preferences of concepts and sub-concepts (see sections II-B, and II-C). This leads to objective-subjective fronts, which can be used by the designers for further investigations. Clusters of preliminary designs, in the fronts, represent concepts. Undesired convergence is avoided by using an interval of acceptance, which is introduced in section II-A. Furthermore, other newly introduced mechanisms allow maintaining spread and diversity of concepts on the front.

The methodology suggested here, does not require the separate generation of concepts' fronts. Evolutionary computations (EC) are used to simultaneously explore and select concepts according to their mixed objective-subjective success.

II. METHODOLOGY

A. Background

A new methodology is developed, which enables a simultaneous evolution of design concepts by EC, and is guided by an interactive Pareto-directed approach. Preliminary designs are evaluated using models. These are linked to concepts, as well as sub-concepts. Design concepts are further assessed by human subjective preferences of concepts and sub-concepts. In contrast to a theoretical Pareto front, the methodology uses ranked non-dominated sets, which are obtained by objective model-based design performance evaluations. These are further manipulated by the subjective evaluations to produce objective-subjective fronts.

To allow a concept-based evolution for the selection of solutions through the use of genetic algorithms, we introduced in [1] some basic notions that are outlined here and further elaborated. Moreover, some new ideas, which result from the Pareto-based motivation, are introduced.

A Sub-Concept (S-C) is an abstract description of a generic part of some potential solutions. Any conceptual solution can be described in terms of its' S-Cs. The S-Cs' categories of the problem are predefined, as well as their allowable combinations for valid solutions. For example, all S-Cs producing a control torque for a manipulator's arm (controllers) are considered as belonging to the same category. Combining control S-Cs alone is not admissible, and an additional category describing the concept's part, which has to be controlled, is required. The allowable combinations of S-Cs' categories are a result of the need to have a solution concept, which completely contains the expected functionality of the actual artefact. All potential solutions, which are related to the same combination of S-Cs, are considered as belonging to a particular concept C. For each sub-concept there is a related set of design parameters, p. A particular design solution, which is considered here, is a preliminary solution, belonging to a distinct concept, and is related to the concept's set of S-Cs, S. The preliminary solution is described by the values of the design parameters, p, which are related to its' S-Cs.

Representing the design space, and its' members, can be done in different manners. We choose to view the space of all possible conceptual designs, as represented by a hierarchical 'and/or' tree. Each concept is an 'and' tree, which can be extracted from the general 'and/or' tree. The nodes involve the related S-Cs. These are organized in a hierarchical order along the tree. We choose to relate the fitness of concepts and S-Cs to the tree hierarchy. Figure 1, in conjunction with table 1, depicts an example of such a hierarchical 'and/or' tree. The tree, in figure 1, represents a space of concepts, as related to a manipulator. It is noted that the 'and' signs are omitted from the figure, and can be traced, by their context, as explained below (overlapping nodes designate 'or').

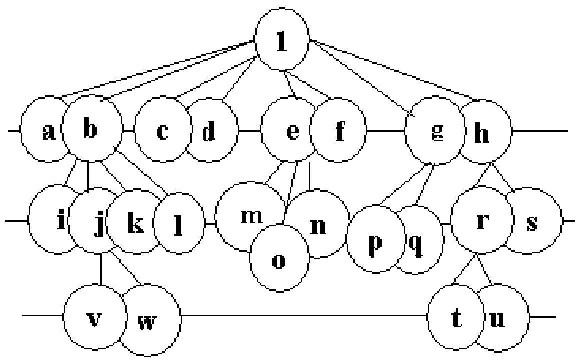

Fig 1. Hierarchical 'and/or' tree of S-Cs

Table 1: Details of Fig 2

S-C	Abstract description of S-C	Level			Level
1	A manipulator	1	l	Prismatic, Revolute	3
a	Redundancy	2	m	Rectangle cross section	3
b	Non-redundancy (two links)	2	n	I-Shaped cross section	3
c	Aluminum-based links	2	o	Circle shaped cross section	3
d	Steel-based links	2	p	PID controller	3
e	Uniform link's cross section	2	q	Pole placement	3
f	Non-uniform links' cross section	2	r	Fuzzy controller	3
g	Linear control	2	s	NN controller	3
h	Non-linear control	2	t	Tri-angle membership fn.	3
i	Prismatic joints	3	u	Trapezoid membership fn.	4
j	Revolving joints	3	v	Elbow up	4
k	Revolute, Prismatic	3	w	Elbow down	4

A valid concept, according to the given example, for a two-degree freedom robotic task, could be a two-link manipulator with PID controllers and an elbow-down configuration. For the above description to be a complete concept, two additional S-Cs should be included. For example, aluminum links with an I-shaped constant cross-section. The solution is therefore $w \wedge c \wedge n \wedge p$, with indices as detailed in table 1. The depth in the tree (indexed with higher values) reflects the level of abstraction.

A Compound-Individual, (C-I) holds the genetic code, as described in [1]. The code consists of all S-Cs and all design parameters, in an 'and/or' structure. It enables the evolution of concepts, and preliminary design parameters, simultaneously. A genetic code is used for competing S-Cs. Decoding the S-Cs competition code produces a number (value of acceptance) within the lower and upper bound of a pre-assumed scale of acceptance. This scale is divided into equal intervals, which are termed Interval of Acceptance (IOA), each designated for a particular competing S-C. Decoding the S-Cs in this way, rather then through a discrete binary method, ensures that winning S-Cs are not easily destroyed. The IOAs point to the winning S-Cs, and their related preliminary design parameters, S_w and p_w, respectively.

The performances, f, of a preliminary design are evaluated, and used for the evolution process. Due to the relation between each preliminary design and its' S-Cs, through the C-I, the success of a preliminary design is translated into a success of its' S-Cs. To evaluate the performance of a preliminary design, a model is employed in accordance with its' associated S-Cs. The performance of a winning preliminary design is utilized to assign fitness to each C-I. This performance-based fitness is an outcome of computations; hence we use the term Machine-based Fitness.

In [2], concepts' preference articulation by a decision-making team (designers), were introduced. The algorithm, presented there, permits the articulation of concepts, and S-Cs' preferences, interactively during the evolution, thus facilitating team brainstorming at the conceptual design stage. The team preferences are restricted to concepts and S-Cs, thus upgrading the use of GAs for conceptual design at the abstract level. The influence of team preferences on the fitness of individuals in the genetic space results in a Human-based Fitness.

In the following, the ideas presented in [1] and [2], are modified to allow a Pareto-directed approach.

B. Machine-based Fitness

B.1 Non-dominancy sorting

The following algorithm assigns a level of non-dominancy (herby termed rank), r, to each individual. The predefined number of ranks is q_r. The individuals of the first rank are assigned with an initial upper (U) fitness bound, as large as the population size, n_p

$$\mathrm{fit}_U^r = n_p, \qquad \text{for} \quad r=1 \tag{1}$$

For subsequent ranks upper fitness bounds are calculated as follows:

$$\mathrm{fit}_U^{r+1} = \mathrm{fit}_U^r - \delta_0, \quad \text{for } r=1,\ldots, q_r-1 \qquad (2$$

Similarly, a lower (L) bound is assigned for each rank according to,

$$\mathrm{fit}_L^r = \mathrm{fit}_U^{r+1} + \varepsilon, \quad \text{for } r=1,\ldots, q_r \qquad (3$$

where $\varepsilon << fit_U^{r+1}$ is separating between adjacent ranks. As a result, each rank has an available fitness span, δ, where,

$$\delta = \delta_0 - \varepsilon \tag{4}$$

The available span is reserved for distributing the fitness of the individuals, of the rank, according to front-based concept sharing, and in-concept niching, as explained in the following.

B.2 Front-based concept sharing

Concept sharing was first introduced in [1], with the goal of preserving concept diversity and preventing a good concept from hindering the evolution of other potential concepts. Here, concept sharing is implemented within each rank. A sharing penalty function for the i-th C-I, belonging to the m-th concept, within the r-th rank is defined as:

$$\phi_i^{r,m} = \frac{0.5\,\delta}{n^r} n^{r,m} \tag{5}$$

where, $n^{r,m}$ is the total number of C-Is belonging to the m-th concept within rank r, and n^r is the size of the population belonging to rank r.

B.3 In-concept front niching

In our approach, fitness sharing is practiced within each concept, rather than within all the population. This preserves diversity within each concept belonging to a particular rank. It is suggested that, for concept-based evolution methodology, two types of niching, genotypic and phenotypic, are worth considering. In this paper we consider a phenotypic in-concept front niching.

For the phenotypic approach, a normalized Euclidean distance-measure, for the i-th and the j-th individuals, belonging to the r-th rank and m-th concept, is computed as follows:

$$d_{ij}^{r,m} = \sqrt{\sum_{n=1}^{n_o} \left(\frac{per_i^n - per_j^n}{per_{best}^n - per_{worst}^n} \right)^2} \tag{6}$$

where, n_o is the number of objectives to be optimized, and per_i^n is the performance of the preliminary design of the i-th individual with respect to the n-th objective. Also, $per_{best}^n = \max(per_i^n)$ and $per_{worst}^n = \min(per_i^n)$, are the best and worst performances within objective n, of the individuals, in rank r and concept m. A sharing function, for the i-th individual with respect to the j-th individual, of the r-th rank and the m-th concept, is computed as:

$$sh_{d_{ij}^{r,m}}^{r,m} = \begin{cases} 1-(d_{ij}^{r,m}/\sigma_{share})^2, & \text{if } d_{ij}^{r,m} \le \sigma_{share} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where,

$$\sigma_{share} = \frac{0.5}{\sqrt[n^{r,m}]{10}} \tag{8}$$

The niche count for each individual i, belonging to the m-th concept, and the r-th rank, is computed by:

$$m_i^{r,m} = \frac{0.5\delta}{n^r} \sum_{j=1}^{n^{r,m}} sh_{d_{ij}^{r,m}}^{r,m} \tag{9}$$

B.4 Machine-based fitness assignment

The fitness of the i-th individual of the r-th rank, is calculated by subtracting from the initially assigned dummy fitness, $fit^r_{D,U}$, the concept-sharing penalty, $\phi_i^{r,m}$, (Eq. 5), and further subtracting the niche count, $m_i^{r,m}$, (Eq. 9). This yields the following expression for the individual's machine-based fitness (MBF):

$$fit_i^r = fit_U^r - \phi_i^{r,m} - m_i^{r,m} \tag{10}$$

It can be seen that the maximal downgrading of the initially assigned individual's fitness is not more than the reserved span (see section II-B1). Finally, C-Is, which are not included within the q_r ranks, are given a fitness, which is lower than $fit_{D,L}^{r=q_r}$. A description of the influence of each component in Eq. 10 is given in figure 2 a & b.

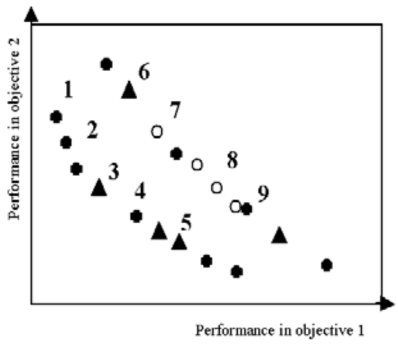

Fig 2.a Objective space presentation

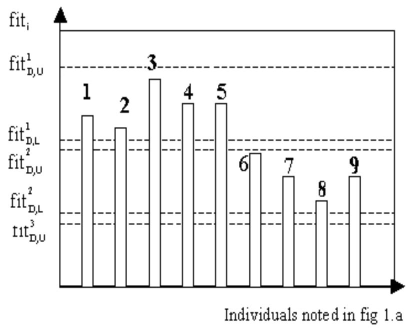

Fig 2.b Machine-based fitness for selected individuals

In figure 2a, two non-dominancy ranks, within the objective space, are shown. Each rank contains several individuals. The individuals' concepts are indicated by circle, cross, and triangle symbols. Also, several individuals are numbered, and referred to in figure 2b. Individuals 1-5, of the first rank (rank 1), are assigned initially the fitness $fit^1_{D,U}$ (see Fig 2b). Individual 3 has the smallest reduction of fitness, in comparison with other members of the front. This is because it belongs to a concept with the smallest number of members in rank 1, and is not as niched as individual 5. Individual 2 belongs to the most populated concept in the first rank, and is more niched in comparison with other individuals of the rank. Therefore, it is the most penalized individual in the rank. Individuals of the second rank, such as 6-9, are dummy fitted with fit^2_U and further re-evaluated by their front-based concept sharing, and in-concept niching, within the 2nd rank. This is demonstrated by figure 2b, as resulting from the individual distribution in rank 2, which is depicted in figure 2a. The MBF procedure is summarized in the following pseudo algorithm.

Assign fitness bounds by Eqs. 1, 2 & 3.
Set r=1
While *$r \leq q_r$*
Find the current non-dominance front

While *not all current front's individuals have been assigned fitness*
ϕ_i^{r,C_m} *= Concept sharing by Eq. 5*
m_{in}^{r,C_m} *= Niche count from in-concept niching by Eq. 9*
MBF= machine-based fitness by Eq. 10
End

Remove current front from population
Set r=r+1
End
for *all individuals not assigned with new rank*
$\mathrm{fit_i} = 0$
end

C. Interactive Human-based Fitness

The interactive preference articulation influences the fitness of the individuals, reflecting the attitude of the team towards the S-Cs and concepts. In [2], weights were used, to employ designers' preferences of concepts and S-Cs, in conjunction with a dynamic goal approach. Here, a logical re-assignment of concept preference is developed, in conjunction with a Pareto paradigm, and the 'and/or' tree design space representation (see section II-A). While automatic evaluations are carried out in conjunction with the entire tree, the subjective preferences are carried out up to a chosen level of abstraction. The team's preferences are accounted for in accordance with their location in the hierarchical tree. This is carried out by the following procedure, which makes sure that human preferences of S-Cs are not contradicting to the hierarchy of the S-Cs. The team may assign weights to some S-Cs of the problem, with values in the interval [-1, 1], where -1 designates pure dislike, and 1 stands for highest preference. S-Cs, with no preference, are automatically assigned with zero weights. A S-C, belonging to the k-th hierarchy, which is manually assigned with a preference is hereby termed SC^{*k}, and its' assigned weight is w_{SC}^{*k}. Each extracted 'and' tree, representing a concept, contains n_A paths. For each path j, the weight of the SC^{*k}, with the lowest k, is marked $w_{\mathrm{SC}}^{*k(j)}$. Branches, below the nodes with $w_{\mathrm{SC}}^{*k(j)}$, are pruned. The weights, of the resulting tree, are used to obtain the concept-weight, H, representing the concept preference. Starting from the leaves of the pruned tree, the weight, w(pr), of each parent node, is calculated by averaging the weights of the children, w(ch). This is further used for calculating the weights of the ancestors up to the root. The weight of a parent node is:

$$\mathrm{w(pr)} = \frac{1}{n_L}\sum_{n=1}^{n_L} \mathrm{w(ch)} \tag{11}$$

where, n_L is the number of the node's children. The concept-weight is re-scaled to produce a Human-Preference-Measure (HPM):

$$\mathrm{HPM} = 1 + \mathrm{H} \tag{12}$$

A combined Human-Machine-Fitness (HMF) is obtained, as follows:

$$\mathrm{HMF}=\begin{cases} \mathrm{fit}_i \cdot \mathrm{HPM} & \text{for } 0 \le \mathrm{HPM} \le 1 \\ \mathrm{fit}_i + (\mathrm{fit}_{max} - \mathrm{fit}_i^{max,m}) \cdot (\mathrm{HPM}-1) & \text{for } 1 < \mathrm{HPM} \le 2 \end{cases} \tag{13}$$

where, fit_{max} is the maximal machine fitness over all individuals within the generation, and $\mathrm{fit}_i^{max,m}$ is the maximal fitness of an individual belonging to a concept m of the generation. Thus, the fitness of an individual is scaled according to the team preferences. Eq. (13) is depicted in figure 3, with an example at HPM=1.3.

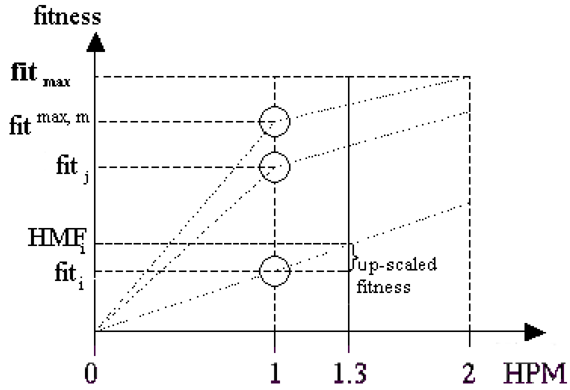

Fig 3. HMF rescaled fitness

D. HMF-based re-ranking

Due to the shuffling of the initially assigned ranks, by the human intervention, as discussed above, the HMF of a large portion of the population may rise rapidly. This can cause exploitation at a too early stage of the evolution. A re-ranking procedure is therefore employed. The new ranking is based on the obtained HMFs (Eq. 13). The predefined number of ranks is maintained as q_r. A new rank, r_{new}, is assigned to each individual i, by the following sorting pseudo algorithm, which also increases the resolution by decreasing the interval for each rank, while maintaining the number of ranks.

for all individuals
    if $\mathrm{fit}_U^1 - 0.5\delta_0(r-1) \ge \mathrm{HMF}_i > \mathrm{fit}_U^1 - 0.5\delta_0\, r$ ***;*** $1,..,q_r$
        $r_{new} = r$
        $\mathrm{fit}_i = \mathrm{fit}_U^1 - \Delta(r_{new}-1)\mathrm{gen}^{\alpha}$
    end

for *all individuals not assigned with new rank*
    $\mathrm{fit}_i = 0$
end

In this sorting algorithm Δ is a predefined fitness interval, 'gen' is the current generation number, and α is a generation-based search pressure parameter. As α increases, the search pressure increases with generation progress. This is due to the increased span between the fitness of individuals belonging to adjacent ranks as evolution moves from one generation to the next.

E. The Algorithm

A pseudo algorithm for interactive concept-based objective-subjective Pareto-directed front is outlined below.

INITIALIZE: *C-I= compound individuals* (section II-A)
While *team discussion continues*
w_{SC}^{*k} =*Interactive team preferences* (section II-C)

While *generation* ≤ *final generation*

As detailed in section II-A:
While *not all individuals' performances computed*
C-I$_d$ = *decode C-I*
S_w = *winning S-Cs by IOAs*
f = *Model-based performances* (S_w)
end

Follow pseudo algorithm of MBF as outlined in section II-B

As detailed in section II-C:
HPM=Human preference measure by Eq.(12)
HMF= Scaled human fitness by Eq. (13)
As detailed in section II-D:
fit =assign final fitness by the sorting algorithm
C-I = Reproduce C-I
C-I = recombine C-I
C-I = Mutate C-I
End

Introduce fronts to the team
End

This algorithm is used in the following examples.

III. CASE STUDIES

To show the applicability of the proposed algorithm, several bi-objective academic examples are used. Each example is designed to demonstrate a certain element of the algorithm. In all of the following examples the same genetic algorithm parameters were maintained, as detailed in table 2.

Table 2: Algorithm's parameters

parameter	value
q_r	8
δ	40
ε	10
n_p	500
Δ	40
α	0.5
pc	0.7
pm	0.03

Where pc, and pm, are the probabilities for crossover and mutation, respectively.

Example 1: Mechanism of IOA

We begin by demonstrating the IOA mechanism, which is the basic idea allowing the evolution of S-Cs by way of the C-I structure. The chosen academic problem has the following objectives:

$$\begin{aligned} f_1 &= x^2 + b \\ f_2 &= (x-2)^2 + b \end{aligned} \tag{14}$$

The problem domain, x, is defined within the interval [-10, +10]. The parameter b may change. Its' changes reflect different models, which are associated with chosen S-Cs. In this particular example, a concept is constructed of only one S-C, hence the number of S-Cs is equal to the number of concepts. The S-Cs are coded in each C-I, with their associated parameters x. The IOAs, of the decoded C-I, determine the winning S-Cs. Figure 4a depicts the S-Cs' performances of a representative portion of the initial population, in the objective space. The initial population of 500 individuals is equally shared by all concepts. The different symbols of rhombus, circle, and cross, correspond to b=0, b=5, and b=15, respectively. In other words, each symbol corresponds to a particular concept. In figure 4b, the 500 individuals are shown, with their indexed number depicted on the vertical axis. The horizontal axis shows the value of acceptance for each individual. The scale of acceptance is divided into three equal IOAs. The lowest, middle and highest IOAs correspond to b=0, b=5, and b=15, respectively. Clearly, the initial population in figure 4b is evenly scattered within the lower and upper bound of the scale of acceptance.

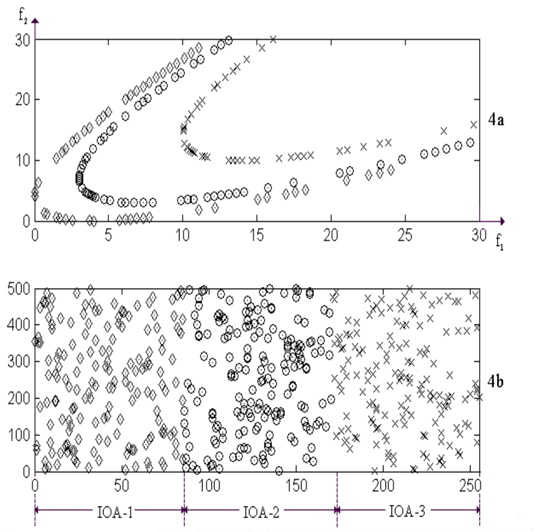

Fig 4 a & b: Initial performances & IOAs

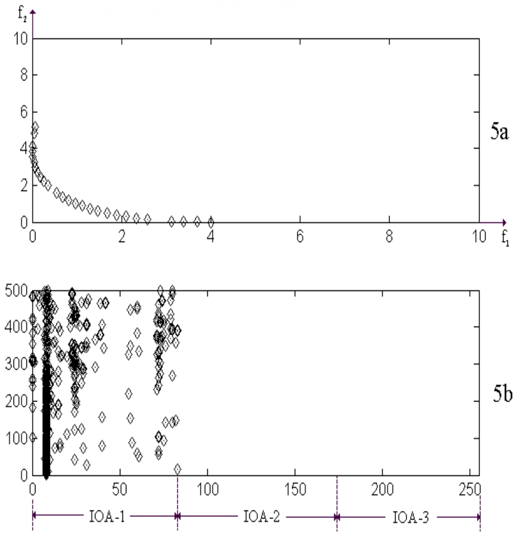

Fig 5a &b: An intense winning S-C

After evolving the population for 7 generations, both the results in the objective space and in the scale of acceptance are changed, as depicted in figure 5. As could be expected, the concept of b=0 has won. In fact it is the only concept currently surviving in the front. The IOA of the winning S-C (here also concept) has a high density of individuals concentrating towards the lowest level of acceptance. This distribution of the population along the scale of acceptance means that the acceptance values of most individuals are far away from the IOAs of the other S-Cs. Hence, they are less susceptible to being destroyed. Figure 6a&b shows the results with the lowest, middle, and highest IOAs, corresponding to b= 5, b=0, and b= 15, respectively. It is clear from the results that the front has not changed, and that the winning individuals aggregate in the vicinity of the mid-value of acceptance, which is the farthest location from the IOAs of the non-winning S-Cs. This is consistent with the findings of figure 5, and with other numerical experimentations not shown here.

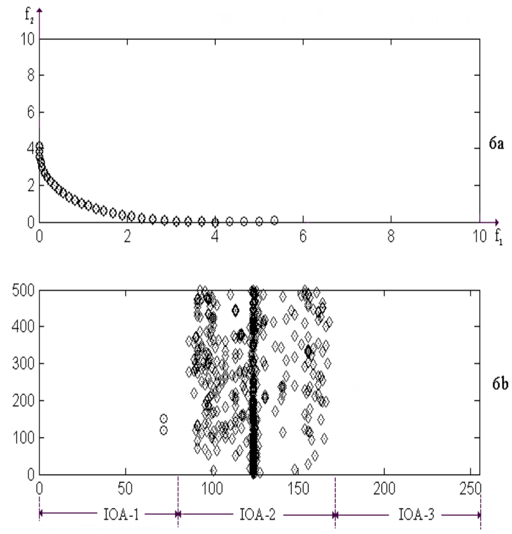

Fig 6 a&b: An intense winning S-C centrally coded

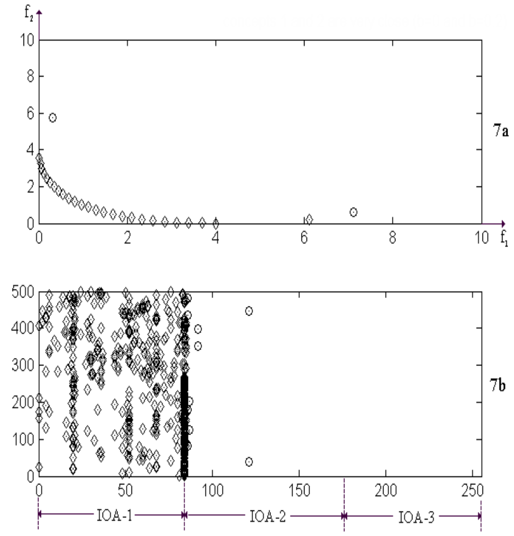

Fig 7 a&b: A moderate winning S-C

In figure 7a&b the experiment of figure 5a&b is repeated, with a replacement of b=5 with b=0.5 (second concept). This replacement causes a lower domination of the first concept (b=0) over the second new concept (b=0.5). Comparing the results of figure 7 with those of figure 5 it is clear that the winning concept has not changed, yet it is more susceptible to changes towards the second concept. In other words, a large portion of the population is concentrating near the IOA of the second concept.

Example 2: Machine-based fitness

The elements of machine-based fitness are examined using another bi-objective problem as defined below. The objectives are:

$$f_1 = x^2 + (a+b)^2$$
$$f_2 = (x-2)^2 + (a+b)^2 \qquad (15)$$

The problem domain, x, is defined within the interval [-10, +10]. To demonstrate concept-based front sharing, and in-front concept niching, four S-Cs are used. Two of the S-Cs have different values for the 'a' parameter (+1, +3), while the other two have different values for 'b' (-3, -1). The four combinations of the above S-Cs are competing concepts. This is clearly an artificially designed case, which allows the demonstration of two concepts sharing the same front, which is characterized by $(a+b)^2 = 0$. It is also noted that the other two concepts could not survive the evolution. The population of C-Is is evolved for 10 generations to produce the front, which is depicted in figure 8. The performances of both winning concepts are shown in the objective space. The two concepts are marked by different symbols (triangles and circles). It can be seen that both concepts have a similar number of representatives in the front, which are scattered along the front. This result is due to the implementation of both front-based concept sharing, and in-concept front niching. Additional experiments show that the results are independent of the initial population.

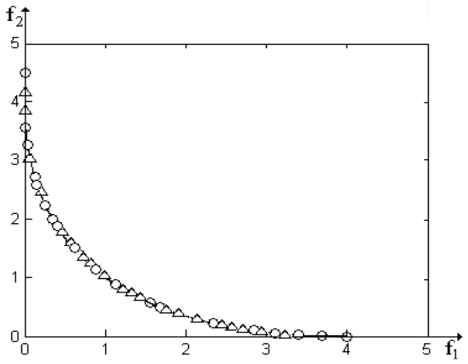

Fig. 8: Identical concepts' front

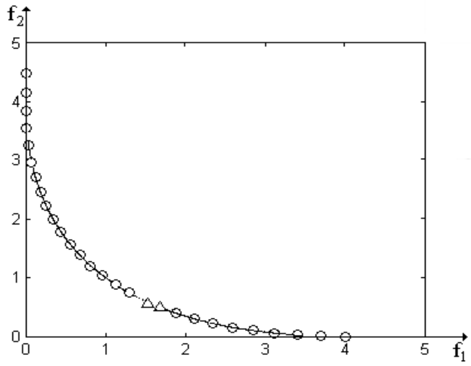

Fig. 9: No in-concept front niching

Unless front-based concept sharing is implemented, the resulting front may be fully taken over by just one concept, depending on the initial population. Using front-based concept sharing, with in-concept front niching limited to one of the concepts (circles), results in a front that is not fully occupied by both concepts. As depicted in figure 9 (after 10 generations), both concepts survived on the front. While concept sharing maintained a balance between the amounts of individuals belonging to each surviving concept, the shown distribution is uneven. All surviving individuals, symbolized with triangles, are concentrated, whereas, those symbolized by a circle are quite evenly distributed.

Example 3: Interactive human-based fitness

Example 1 is reused here, with minor changes, to show the influence of human intervention. Two S-Cs are used, one corresponds to b=0 and the other to b=5. When there are no S-Cs' preferences, then HPM=1, for both concepts. In such a case no upgrading of the machine-based fitness occurs. The resultant Pareto front, corresponding to the winning concept (b=0), is shown in figure 10.

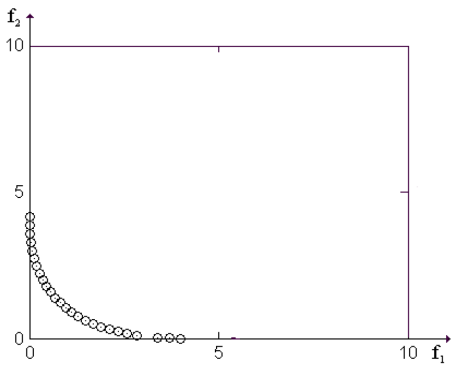

Fig 10: Winning concept's front

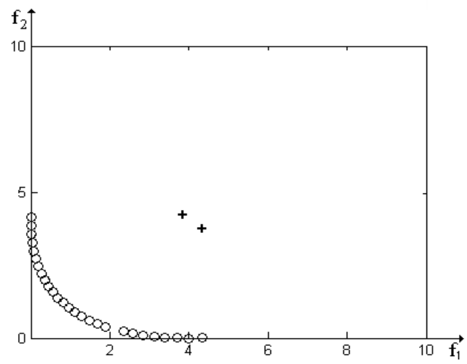

Fig 11: Concepts' fronts with $w_2^{*1} = 0.4$

Gradually increasing the preference of the disappearing concept (b=5), leads to the results depicted in figures 11 & 12. This is achieved by assigning w_2^{*1}, the values of 0.4, and 0.7, for the cases of figures 11 & 12, respectively.

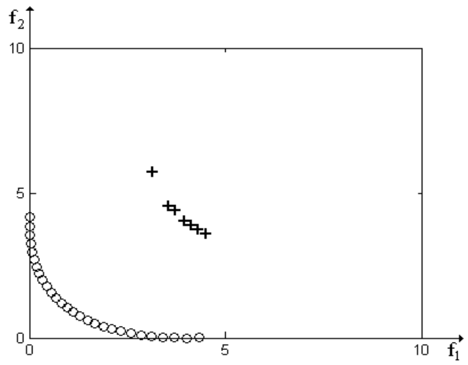

Fig 12: Concepts' fronts with $w_2^{*1} = 0.7$

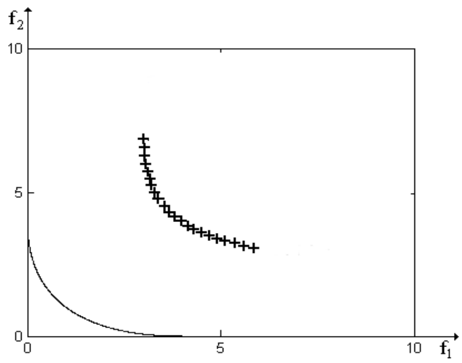

Fig 13: High preference to the inferior concept

The results, depicted in figures 13, were obtained by changing both the preference of the first and second S-Cs. This is achieved by assigning w_2^{*1}, and w_1^{*1}, the values of 1.0, and -0.5, respectively. The later assignment causes the entire front to change to a subjective front, with the second concept becoming the winning one. The location of the original objective front is shown in figures 12, as a reference.

Example 4: Concept-based evolution

The objectives, used in this academic example, are:

$$\begin{aligned} f_1 &= x^2 + 5b + 10 \\ f_2 &= (x-4)^2 + c(b-1)x \end{aligned} \tag{16}$$

The problem domain, x, is defined within the interval [-10, +10]. The space consists of four concepts, which are outlined in table 3. The concepts are composed of four S-Cs, which are characterized by: c=-3, c= -4, b=+2, and b=+3.

Table 3: Summary of concepts and their legend

Concept #	c values	b values	Symbol
1	- 3	+2	circle
2	- 4	+2	star
3	- 4	+3	rhombus
4	- 3	+3	plus

In the first simulation, which provided the results shown in figure 14, there are no human preferences assigned to the S-Cs. It can be seen that concept # 1 (plus) did not survive at all, while the others share the resulting front. At the top part of the front, concept-based front sharing allows the mutual survival of concepts # 1 & 2 (circles & stars). Descending along the front, it contains only one dominating concept (stars), and then again, at the lower part, it contains another concept (rhombus).

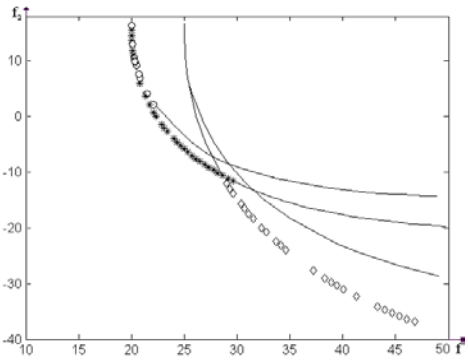

Fig 14: Objective multi-concept front

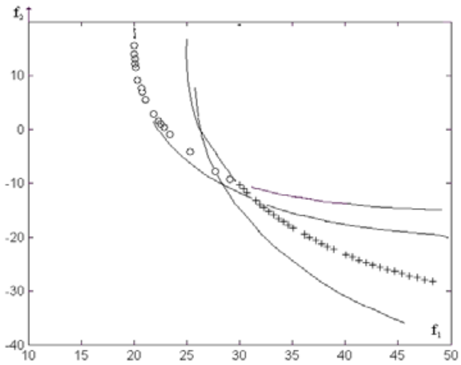

Fig 15: Subjective multi-concept front

To demonstrate the effect of human preferences, the following situation is examined. The weight of the S-C characterized by c= -3 is assigned with a value of 1.0 (the highest preference possible), and the weight for c= -4 is chosen as –0.6. These preferences cause the concepts, associated with c=-3 (concepts 1 & 4), to be preferred over those associated with c=-4 (concepts 2 & 3). The results of the evolution are shown in figure 15. Figure 15 is a result of a Pareto-directed interactive concept-based evolution, which is achieved by preferring different S-Cs. Comparing figure 15 with figure 14, it can be seen that the winning concepts are different. This is due to influence of the subjective preference articulation.

Example 5: Hierarchy of S-Cs

To examine the influence of the S-Cs' hierarchy, the following objectives are used:

$$\begin{aligned} f_1 &= x^2 + b \cdot c \\ f_2 &= (x-2)^2 + b \cdot d \end{aligned} \tag{17}$$

The search interval for x is kept as in the previous examples. Eight concepts based on ten S-Cs are used. The S-Cs, within the hierarchy arrangement of the 'and/or' tree, are depicted in figure 16. The parameter 'b' characterizes the highest S-C of the hierarchy. The combination of b=1, c=3 and d=1, is an example of a collection of parameters, which distinguishes a model of a potential solution.

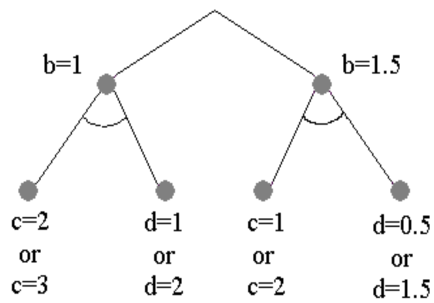

Fig 16: S-Cs' arrangement within the 'and/or' tree

Table 4 provides a list of concepts and their associated symbols as used in the following figures.

Table 4: Summary of concepts and their legend

Concept #	b values	c values	d values	Symbol
1	1	2	1	○
2	1	3	2	▷
3	1	2	2	✳
4	1	3	1	□
5	1.5	1	0.5	+
6	1.5	2	1.5	◆
7	1.5	1	1.5	◁
8	1.5	2	0.5	▼

Figure 17 shows a part of the initial population. The eight concepts are distributed in the objective space according to their performances, as calculated by Eq. 17.

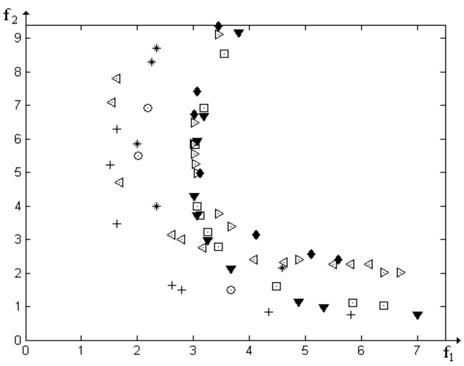

Fig 17: Initial distribution of concepts

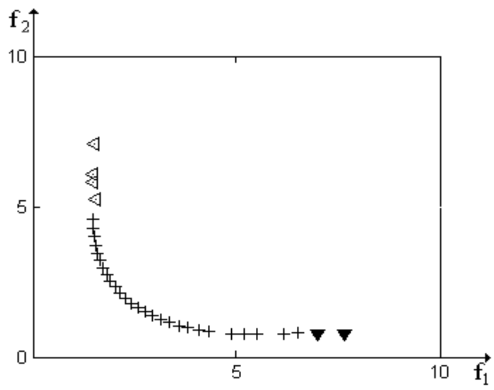

Fig 18: Machine-based front

Figure 18 depicts the resulting front after seven generations. It shows that three concepts survived (concepts # 5,7,8). The winning concepts are associated with the S-C of b=1.5.

Figure 19 shows the resulting fronts after seven generations, with preference assignment. A weight of $w_1^{*1} = 0.6$ for the S-C of b=1, is used. Clearly, this causes a change from the front of figure 17. In addition to concept # 5, which belongs to the branch of b=1.5, a second concept survived belonging to the branch with b=1(concept # 1).

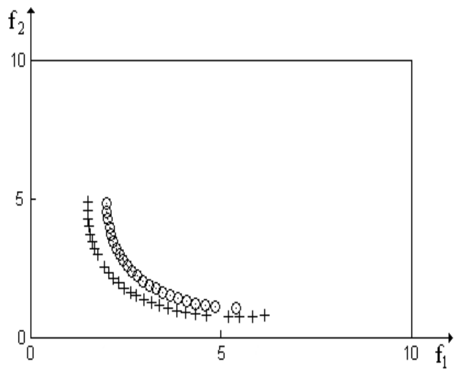

Fig 19: Subjective front - $w_1^{*1} = 0.6$

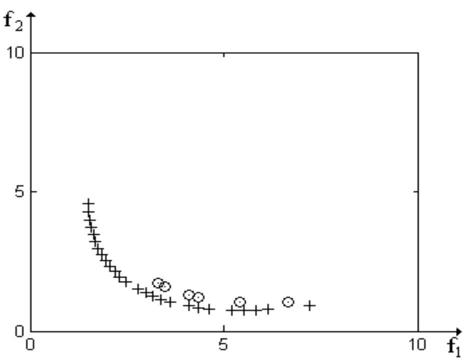

Fig 20: Subjective front - $w_2^{*2} = 0.6$

Figure 20 shows the results, with a change of preference of a S-C, which belongs to a lower hierarchy. The S-C associated with d=1 (belonging to the branch of b=1) is assigned a preference weight, $w_2^{*2} = 0.6$. This assignment causes the survival of concept # 1, yet the resulting front is not as full, in comparison with that of figure 19. This is due to the lower location of the preferred S–C within the hierarchy, as implemented in Eq. 11. Furthermore, the surviving cases of concept #1 appear from the lower part of the front. This is consistent with the ranking of the various cases of the concept. When the S-Cs, associated with c=2 and d=1, are both assigned with weights (w_1^{*2}, w_2^{*2}) of 0.6, the result is similar to the one depicted in figure 19. Increasing weight w_2^{*1} (the b=1 branch) to 1.0, a further increase in the survivability of concepts, belonging to the b=1 branch, takes place, as shown in figure 21.

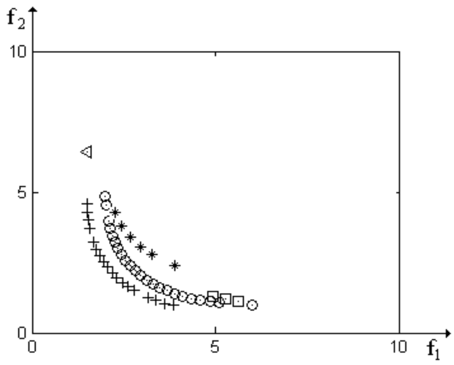

Fig 21: Subjective front - $w_1^{*1} = 1.0$

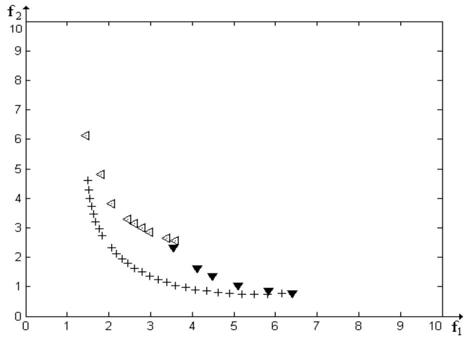

Fig 22: Subjective front - $w_2^{*1} = 0.6$

Three out of the four concepts, belonging to that branch, appear in the resulting objective-subjective front. The forth concept did not appear, due to its low performance.

If the branch of b=1.5 is given a higher preference ($w_2^{*1} = 0.6$), with no preference to b=1, a second front is surviving along with a front similar to the initial one. This can be seen by comparing figure 22 with figure 18.

Any concept can be retained in the evolution by changing the preferences of its' relevant S-Cs', and those of the competing concepts. For example, concept #6, which has not survived so far, can be elevated by a subjective decision. This can be done by assigning preference weights of 0.6 to d=2 and c=1.5, as well as assigning a value of –0.4 to the competing branch of b=1.0, and the competing S-Cs of the branch of b=1.5. The resulting front of these assignments, which contains concept # 6 alone, is depicted in figure 23.

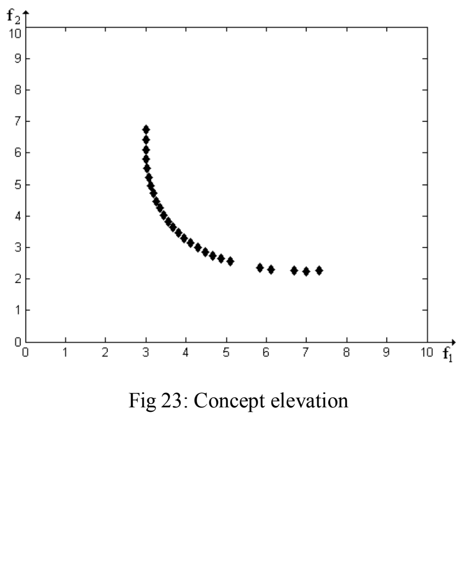

Fig 23: Concept elevation

IV. SUMMARY AND CONCLUSIONS

A concept-based evolutionary method, which strengthens symbiosis between computers and humans, in exploring engineering solutions to multi-objective design problems, is presented. It is developed to simultaneously explore concepts and make a selection based on evolving Pareto-directed fronts. The suggested procedure involves some unique aspects such as: front-based concept sharing, and in-concept front niching. These special features allow several concepts to compete during the evolution and survive within the evolving fronts. This is in contrast with methods that evolve each concept at a time, and use a post-evolution creation of a mixed front. Such methods require a multi-start strategy that is not efficient with an increase number of concepts. Moreover, they do not allow progressive concepts' preference articulation. The current methodology, allows a more controlled search of winning concepts, and their associated fronts, by progressive interactivity.

In contrast to a theoretical Pareto front, the methodology uses ranked non-dominated sets, which are obtained by objective model-based design performance evaluations. These are further manipulated by subjective evaluations to produce objective-subjective fronts.

The suggested procedure maintains a balance between the role of computers and humans in the decision process. Furthermore, it allows human-machine communication to take place at the level of concepts, which is natural for humans. The role of the computer is based on its' irreplaceable ability for intensive calculations. For a chosen concept, concrete models, analyses, and calculations, can be made, and computer-based parametric studies may improve the design through the examination of preliminary designs clustered according to concepts.

Several examples are given, which demonstrate the performance of our concept-based method. The results show the applicability of the method and its' potential in bridging the communication gap between machines and humans. Future work may include an extension of our methodology to robust conceptual design.

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