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First Results of an Evolutionary Approach for the Entity Refactoring Set Selection Problem

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Abstract

Refactoring is a commonly accepted technique to improve the structure of object oriented software. The paper presents a multi-objective approach of the Entity Refactoring Set Selection Problem (ERSSP) by treating the cost constraint as an objective and combining it with the effect objective. A weighted objective genetic algorithm is proposed and run on an experimental didactic case study. The results for several experiments with different weight parameter values are discussed too.

1. Introduction

Software systems continually change as they evolve to reflect new requirements, but their internal structure tends to decay. Refactoring is a commonly accepted technique to improve the structure of object oriented software [5]. Its aim is to reverse the decaying process in software quality by applying a series of small and behaviour-preserving transformations, each improving a certain aspect of the system [5].

ERSSP is an example of a Feature Subset Selection (FSS) search problem in SBSE field, that identifies the optimal set of refactorings that may be applied to software entities, such that several objectives are kept or improved. ERSSP is a part of larger problem that dicusses the different types of strategies that may be applied when refactoring. One of the aspects is represented by the case when a set of the most efficient refactorings have to be identified, which is the case of ERSSP. The paper shortly presents a formal definition of the MOERSSP and performs a proposed weighted objective genetic algorithm on an experimental didactic case study. In order to identify a single refactoring that may be applied to a software entity, MOERSSP treates the *cost* constraint as an objective and combines it with the *effect* objective. Obtained results for our case study with different weight paramenter values are presented and discussed.

The rest of the paper is organized as follows: Section 2 presents the formal definition of the studied problem, while Section 3 shortly reminds the Multi-Objective Optimization Problem (MOOP). The proposed approach and several details related to the genetic operators of the genetic algorithm are described in Section 4. A short description of the Local Area Network simulation source code used to validate our approach is provided in Section 5. The obtained results for the studied source code are presented and compared in Section 6. Recent related work are reminded in Section 7. The paper ends with conclusions and future work.

2. ERSSP Definition

The complete definition for the ERSSP is presented in [2]. In order to understand the problem a brief summary is given here. Let $SE = \{e_1, \ldots, e_m\}$ be a set of software entities, i.e., a class, an attribute from a class, a method from a class, a formal parameter from a method or a local variable declared in the implementation of a method. The weight associated with each software entity $e_i, 1 \leq i \leq m$ is kept by the set $Weight = \{w_1, \ldots, w_m\}$, where $w_i \in [0, 1]$ and $\sum_{i=1}^{m} w_i = 1$.

A set of possible relevant chosen refactorings [5] that may be applied to different types of software entities of SE is gathered up through $SR = \{r_1, \ldots, r_t\}$. There are various dependencies between such transformations when they are applied to the same software entity, a mapping emphasizing them being defined by:

$rd : SR \times SR \times SE \rightarrow$
$\{\mathbf{B}efore, \mathbf{A}fter, \mathbf{A}lways\mathbf{B}efore, \mathbf{A}lways\mathbf{A}fter, \mathbf{N}ever, \mathbf{W}henever\}$,

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$$rd(r_h, r_l, e_i) = \begin{cases} \text{B}, & \text{if } r_h \text{ may be applied to } e_i \text{ only before } r_l, r_h < r_l \\ \text{A}, & \text{if } r_h \text{ may be applied to } e_i \text{ only after } r_l, r_h > r_l \\ \text{AB}, & \text{if } r_h \text{ and } r_l \text{ are both applied to } e_i \text{ then } r_h < r_l \\ \text{AA}, & \text{if } r_h \text{ and } r_l \text{ are both applied to } e_i \text{ then } r_h > r_l \\ \text{N}, & \text{if } r_h \text{ and } r_l \text{ cannot be both applied to } e_i \\ \text{W}, & \text{otherwise, i.e., } r_h \text{ and } r_l \text{ may be both applied to } e_i \end{cases},$$

where $1 \leq h, l \leq t,\ 1 \leq i \leq m.$ The effort involved by each transformation is converted to cost, described by the function $rc : SR \times SE \rightarrow Z.$ Changes made to each software entity $e_i, i = \overline{1,m}$ by applying the refactoring $r_l, 1 \leq l \leq t$ are stated and a mapping is defined: $effect : SR \times SE \rightarrow Z.$ The overall effect of applying a refactoring $r_l, 1 \leq l \leq t$ to each software entity $e_i, i = \overline{1,m}$ is defined by the mapping $res : SR \rightarrow Z.$ The goal is to find a subset of refactorings $RSet$ such that for each entity $e_i, i = \overline{1,m}$ there is at least a refactoring $r \in RSet$ that may be applied to it, i.e., $e_i \in SE_r$. Thus, ERSSP is the identification problem of the most appropriate refactorings that may be applied to each software entity such that several objectives are kept or improved, like the minimum total cost and the maximum overall effect on the affected software entities.

3. MOOP Model

MOOP is defined in [9] as the problem of finding a decision vector $\vec{x} = (x_1, \ldots, x_n)$, which optimizes a vector of M objective functions $f_i(\vec{x})$ where $1 \leq i \leq M$, that are subject to inequality constraints $g_j(\vec{x}) \geq 0$, $1 \leq j \leq J$ and equality constraints $h_k(\vec{x}) = 0$, $1 \leq k \leq K$. A MOOP may be defined as:

$$maximize\{F(\vec{x})\} = maximize\{f_1(\vec{x}), \ldots, f_M(\vec{x})\},$$

with $g_j(\vec{x}) \geq 0, 1 \leq j \leq J$ and $h_k(\vec{x}) = 0, 1 \leq k \leq K$ where $\vec{x}$ is the vector of decision variables and $f_i(\vec{x})$ is the i-th objective function; and $g(\vec{x})$ and $h(\vec{x})$ are constraint vectors.

There are several ways to deal with a multi-objective optimization problem. In this paper the weighted sum method [6] is used.

Let us consider the objective functions $f_1, f_2, \ldots, f_M$. This method takes each objective function and multiplies it by a fraction of one, the "weighting coefficient" which is represented by $w_i, 1 \leq i \leq M$. The modified functions are then added together to obtain a single fitness function, which can easily be solved using any method which can be applied for single objective optimization.

Mathematically, the new mapping may be written as:

$$F(\vec{x}) = \sum_{i=1}^{M} w_i * f_i(\vec{x}),\ 0 \leq w_i \leq 1,\ \sum_{i=1}^{M} w_i = 1.$$

3.1. MOERSSP Formulation

Multi-objective optimization often means to compromise conflicting goals. For our MOERSSP formulation there are two objectives taken into consideration in order to maximize refactorings effect upon software entities and minimize required cost for the applied transformations. Current research treats cost as an objective instead of a constraint. Therefore, the first objective function defined below minimizes the total cost for the applied refactorings, as:

$$minimize\left\{f_1(\vec{r})\right\} = \left\{\sum_{l=1}^{t}\sum_{i=1}^{m} rc(r_l, e_i)\right\},$$

where $\vec{r} = (r_1, \ldots, r_t)$. The second objective function maximize the total effect of applying refactorings upon software entities, considering the weight of the software entities in the over all system, like:

$$maximize\left\{f_2(\vec{r})\right\} = \left\{\sum_{l=1}^{t}\sum_{i=1}^{m} w_i * effect(r_l, e_i)\right\},$$

where $\vec{r} = (r_1, \ldots, r_t)$.

The goal is to select a subset of entities for each proposed refactoring that results in the minimum total cost and the maximum effect upon affected software entities. In order to convert the first objective function to a maximization problem in the MOERSSP, the total cost is subtracted from MAX, the biggest possible total cost, as it is shown below:

$$maximize\left\{f_1(\vec{r})\right\} = \left\{MAX - \sum_{l=1}^{t}\sum_{i=1}^{m} rc(r_l, e_i)\right\},$$

where $\vec{r} = (r_1, \ldots, r_t)$. The final fitness function for MOERSSP is defined by aggregating the two objectives and may be written as:

$$F(\vec{r}) = \alpha \cdot f_1(\vec{r}) + (1 - \alpha) \cdot f_2(\vec{r}),$$

where $0 \leq \alpha \leq 1.$

4. Proposed Approach Description

The decision vector $\vec{S} = (S_1, \ldots, S_t), S_l \subseteq SE \cup \phi, 1 \leq l \leq t$ determines the entities that may be transformed using the proposed refactorings set SR . The item S_l on the l-th position of the solution vector represents a set of entities that may be refactored by applying the l-th refactoring from SR, where each entity $e_{l_u} \in SE_{r_l}, e_{l_u} \in S_l \subseteq SE \cup \phi, 1 \leq u \leq q, 1 \leq q \leq m, 1 \leq l \leq t$. This means it is possible to apply more than once different refactorings to the same software entity, i.e., distinct gene values from the chromosome may contain the same software entity.

A steady-state evolutionary algorithm was applied here, a single individual from the population being changed at a time. The best chromosome (or a few best chromosomes) is copied to the population in the next generation. Elitism can very rapidly increase performance of GA, preventing to lose the best found solution. A variation is to eliminate an equal number of the worst solutions, i.e. for each best chromosome kept within the population a worst chromosome is deleted.

4.1. Genetic Operators

The parameters used by the evolutionary approach are as follows: mutation probability 0.7 and crossover probability 0.7. Different number of generations and of individuals are used: number of generations 10, 50, 100, 200 and number of individuals 20, 50, 100, 200. The value of α used while aggregating the objectives was set to 0.5 which gives the same importance to both objectives.

For the *crossover operator* a simple one point crossover scheme is used. A crossover point is randomly chosen. All data beyond that point in either parent string is swapped between the two parents.

For example, if the two parents are: $parent_1 = [ga[1,7],\ gb[3,5,10],\ gc[8],\ gd[2,3,6,9,12],\ ge[11],\ gf[13,4]]$ and $parent_2 = [g1[4,9,10,12],\ g2[7],\ g3[5,8,11],\ g4[10,11],\ g5[2,3,12],\ g6[5,9]]$ and the cutting point is 3, the two resulting offsprings are: $offspring_1 = [ga[1,7],\ gb[3,5,10],\ gc[8],\ g4[10,11],\ g5[2,3,12],\ g6[5,9]]$ and $offspring_2 = [g1[4,9,10,12],\ g2[7],\ g3[5,8,11],\ gd[2,3,6,9,12],\ ge[11],\ gf[13,4]]$.

Mutation Operator used here exchanges the value of a gene with another value from the allowed set. In other words, mutation of i-th gene consists of adding or removing a software entity from the set that denotes the i-th gene. We have used 11 mutations for each chromosome, number of genes being 6.

For instance, if we have the chromosome $parent = [ga[1,7],\ gb[3,5,10]\ gc[8],\ gd[2,6,9,12]\ ge[12]\ gf[13,4]]$ and we chose to mutate the fifth gene, then a possible offspring may be $parent = [ga[1,7]\ gb[3,5,10]\ gc[8]\ gd[2,6,9,12]\ ge[\mathbf{10},12]\ gf[13,4]]$ by adding the *10*-th software entity to the *5*-th gene.

4.2. Data Normalization

Normalization is the procedure used in order to compare data having different domain values. It is necessary to make sure that the data being compared is actually comparable. Normalization will always make data look increasingly similar. An attribute is normalized by scaling its values so they fall within a small-specified range, e.g., 0.0 to 1.0.

As we have stated above we would like to obtain a subset of refactorings to be applied to each software entity from a given set of entities, such that we obtain a minimum cost and a maximum effect. The cost for an applied refactoring to an entity is between 0 and 100. At each step of the selection the res function is considered. We must normalize the cost of applying the refactoring, i.e., rc mapping, and the value of the res function too. Two methods to normalize the data: *decimal scaling* for the rc mapping and *min-max normalization* for the value of the res function have been used here.

5. Case Study: LAN Simulation

The algorithm proposed was applied on a simplified version of the Local Area Network (LAN) simulation source code, that was presented in [3]. Figure 1 shows the class diagram of the studied source code. It contains 5 classes with 5 attributes and 13 methods, constructors included.

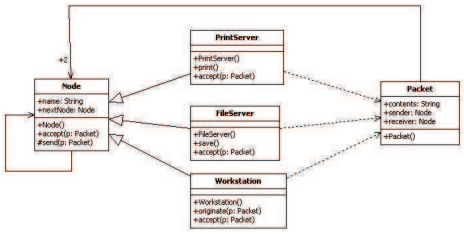


Figure 1. Class diagram for LAN simulation

Thus, for the studied problem the software entity set is defined as: $SE = \{c_1, ..., c_5, a_1, ..., a_5, m_1, ..., m_{13}\}$. The chosen refactorings that may be applied are: *renameMethod, extractSuperClass, pullUpMethod, moveMethod, encapsulateField, addParameter*, denoted by the set $SR = \{r_1, \ldots, r_6\}$ in the following. The dependency relationship between refactorings is defined in what follows: $\{(r_1, r_3) = B,\ (r_1, r_6) = AA,\ (r_2, r_3) = B,\ (r_3, r_1) = A,\ (r_6, r_1) = AB,\ (r_3, r_2) = A,\ (r_1, r_1) = N,\ (r_2, r_2) = N,\ (r_3, r_3) = N,\ (r_4, r_4) = N,\ (r_5, r_5) = N,\ (r_6, r_6) = N\}$. For the res mapping, values were computed for each refactoring, by using a specified weight for each existing and possible affected software entity, as it was defined in Section 2. The value of the res function for each refactoring is: 0.4, 0.49, 0.63, 0.56, 0.8, 0.2.

Here, the cost mapping rc is computed as the number of the needed transformations, therefore related entities may have different costs for the same refactoring. Each software entity has a weight within the entire system, but $\sum_{i=1}^{23} w_i = 1$. Due to the space limitation, intermediate data for other mapping (e.g., effect) was not included. For effect mapping, values were considered to be numerical data, denoting estimated impact of refactoring applying.

6. Practical Experiments for the Proposed Approach

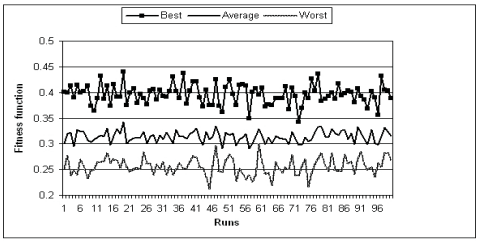
The algorithm was run 100 times and the best, worse and average fitness values were recorded. The following subsections reveal the obtained results for different values of the α parameter, by balancing or not the weight for the studied objectives. The results are summarized and discussed in the last subsection. The run experiments have worked with the α parameter having different values, like: 0.3 and 0.5.

Therefore, the fitness function is rewritten by replacing the α paramater consequently, within the formula:

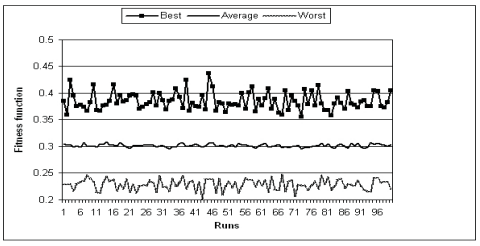
$F(\vec{r}) = \alpha \cdot f_1(\vec{r}) + (1-\alpha) \cdot f_2(\vec{r})$, where $\vec{r} = (r_1, \ldots, r_m)$.

6.1. Equal Weights: $\alpha = 0.5$

A first experiment proposes equal weights, i.e., $\alpha = 0.5$, where the final effect (res function) has the same relevance as the implied cost (rc mapping) of the applied refactorings. Figure 2 presents the 10 generations evolution of the fitness function (best, worse and average) for 20 chromosomes populations (Figure 2(a)) and 200 chromosomes populations (Figure 2(b)).



(a) Experiment with 10 generations and 20 individuals with eleven mutated genes



(b) Experiment with 10 generations and 200 individuals

Figure 2. The evolution of fitness function (best, worse and average) for 20 and 200 individuals with 10 generations

It is easy to see that there is a strong struggle between chromosomes in order to breed the best individual. In the 20 individuals populations the competition results in different quality of the best individuals for various runs, from very weak to very good solutions. The 20 individuals populations runs have a few very weak solutions, worse than 0.35, but there are a lot of good solutions, i.e., 22 chromosomes with fitness better than 0.41. Compared to the former populations, the 200 chromosomes populations breed closer best individuals, since there is no chromosome with fitness value worse than 0.35, but the number of good chromosomes is smaller than the one for 20 individuals populations, i.e., 8 chromosomes with fitness better than 0.41 only. The data for the worst chromosomes reveals similar results, since for the 200 individuals populations there is no chromosome with fitness better than 0.25, while for the 20 chromosomes populations there is a large number of worse individuals better than 0.25. This situation outlines an intense activity in smaller populations, compared to larger ones, where diversity among individuals reduces the population capability to quickly breed better solutions.

The number of chromosomes with fitness value better than 0.41 for the studied populations and generations is captured by Figure 3. It shows that smaller populations with poor diversity among chromosomes have a harder competition within them and more, the number of eligible chromosomes increases quicker for smaller populations than for the larger ones. Therefore, for the 20 chromosomes populations with 200 generations evolution all 100 runs have shown that the best individuals are better than 0.41, while for 200 individuals populations with 200 generations the number of best chromosomes better than 0.41 is only 53.

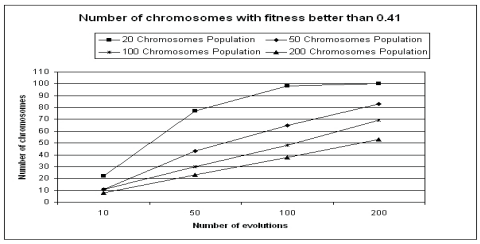


Figure 3. The evolution of the number of chromosomes with fitness better than 0.41 for the 20, 50, 100 and 200 individual populations

For the recorded experiments, the best individual for 200 generations was better for 20 chromosomes populations (with a fitness value of 0.4793) than the 200 individuals populations (with a fitness value of just 0.4515). Various runs as number of generations, i.e., 10, 50, 100 and 200 generations, show the improvement of the best chromosome.

Thus, the best individual fitness value for 10 generations is 0.43965 for 20 individuals populations and 0.43755 for 200 chromosomes populations. This means in small populations (with few individuals) the reduced diversity among chromosomes may induce a harsher struggle compared to large populations (with many chromosomes) where the diversity breeds weaker individuals. As it was said before, after several generations smaller populations produce better individuals (as number and quality) than larger ones, due to the poor populations diversity itself.

The best individual obtained allows to improve the structure of the class hierarchy. Therefore, a new `Server` class is the base class for `PrintServer` and `FileServer` classes. More, the signatures of the `print` method from the `PrintServer` class and the `save` method from the `FileServer` class are changed and then both renamed to

process. The accept method is pulled up to the new Server class. The two refactorings applied to the print and save methods ensure their polymorphic behaviour. The correct access to the class fields by encapsulating them within their classes is enabled. The current solution representation allows to apply more than one refactoring to each software entity, i.e., method print from PrintServer class is transformed by two refactorings, *addParameter* and *renameMethod*.

6.2. Different Weights: $\alpha = 0.3$

Another experiment with different weights, i.e., $\alpha = 0.3$, where the final effect (res function) has a greater relevance than the implied cost (rc mapping) of the applied refactorings is presented below.

Figure 4 shows the the number of chromosomes better than 0.298 for the 20, 50, 100 and 200 individuals populations with 10, 50, 100 and 200 generations. It shows the grouping of the eligible chromosomes for the 100 and 200 individuals populations for each number of generations. The solutions for the 20 individuals populations for the studied number of generations keep their good quality, since the number of eligible chromosomes remains higher than any individuals population recorded by the experiment.

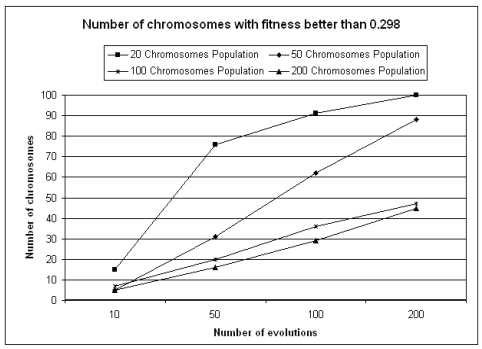


Figure 4. The evolution of the number of chromosomes with fitness better than 0.298 for the 20, 50, 100 and 200 individuals populations, with $\alpha = 0.3$

The experiment shows good results in all 100 runs as quality and number for the studied individuals populations and number of generations. In the 200 generations runs for 200 chromosomes populations the greatest value of the fitness function was 0.33426 (with 45 individuals with the fitness > 0.298) while in the 200 evolutions experiments for 50 individuals populations the best fitness value was not more than 0.32772 (88 individuals with the fitness > 0.298). But the best chromosome was found in the experiment with 200 generations and 20 individuals having the value 0.33587 (with all individuals with the fitness > 0.298).

The best individual obtained by this solution representation makes only small changes to the structure of the class hierarchy. Its analysis allows to extract a base class for the PrintServer and FileServer classes. Therefore, a new class named Server is added to the source code. The addParameter refactoring was not suggested such that the signature for print method from PrintServer class and for save method from FileServer class are changed in order to allow the corresponding accept methods from the PrintServer and FileServer classes to be pulled up. More, no appearance for the encapsulatedField refactoring have been recorded.

6.3. Discussion

Current paper presents the results of the proposed approach in Section 4 for three different value for the α parameter, i.e., 0.3, 0.5. A chromosome summary of the obtained results for all experiments is given below:

- $\alpha = 0.3$, $bestFitness = 0.33587$ for 20 $chromosomes$ and 200 $generations$
  - $bestChrom = [[10, 22, 21, 19, 15], [3, 2], [21, 19, 10, 16, 17, 13, 11, 14, 12], [19, 10, 22, 11, 13, 16], [\Phi], [21, 22]]$
- $\alpha = 0.5$, $bestFitness = 0.4793$ for 20 $chromosomes$ and 200 $generations$
  - $bestChrom = [[20, 13, 19, 11], [1, 2], [15, 10, 20, 17, 19, 13, 12], [12, 11, 15, 14, 21], [6, 8, 9], [22, 12, 18, 17, 13, 14, 15]]$

The experiment for $\alpha = 0.3$ should identify those refactorings for which the cost has a lower relevance than the overall impact on the applied software entities. But, the obtained best chromosome obtained has the fitness value 0.33587, loer than the best fitness value for the $\alpha = 0.5$ chromosome, i.e., 0.4793. This shows that an agreggated fitness function with a higher weight for the overall impact of the applied refactorings unbalance the fitness function. Therefore, there are not too many key software entities to be refactored by a such an experiment.

Balancing the fitness values for the studied experiments and the relevance of the suggested solutions, we consider the $\alpha = 0.5$ experiment is more relevant as quality of the results, than the other analyzed experiments. Figure 5 highlights the changes in the class hierarchy for the $\alpha = 0.5$.

7. Obtained Results by Others

Fatiregun et al. [4] applied genetic algorithms to identify transformation sequences for a simple source code, with 5 transformation array, whilst we have applied 6 distinct refactorings to 23 entities. Seng et al. [8] apply a weighted

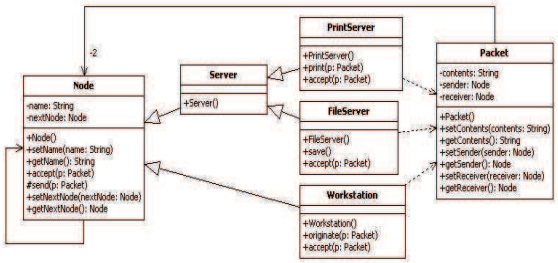


Figure 5. The class diagram for the LAN Simulation source code, with $\alpha = 0.5$

multi-objective search, in which metrics are combined into a single objective function. An heterogeneous weighed approach is applied here, since the weight of software entities in the overall system and refactorings cost are studied.

Mens et al. [7] propose the techniques to detect the implicit dependencies between refactorings. Their analysis helped to identify which refactorings are most suitable to LAN simulation case study. Our approach considers all relevant applying of the studied refactorings to all entities.

Bowman et al. [1] discuss the class responsibility assignment using a multi-objective optimization approach. The goal is to optimize the coupling and cohesion of a given class diagram based on five distinct measures [1]. Although a single objective optimization problem suggests a unique optimal solution, the approach proposed by the authors offers a large set of solutions that, when evaluated, produces vectors whose components represent tradeoffs in the objective space. Similar to this we focus on two objectives. We study the final effect of the applied refactorings but we pay attention to the involved costs too. In this way we try to obtain a solution that is acceptable, with a positive impact on the internal structure of the source code and with low costs too.

8. Conclusions and Future work

The paper defines the MOERSSP by treating the *cost* constraint as an objective and combining it with the *effect* objective. The results of a proposed weighted objective genetic algorithm on an experimental didactic case study are presented and discussed. Furthermore, a thoroughly study will address a larger set of objectives, greater than two which is presented here. Furthermore, a thoroughly study will address a larger set of objectives, greater than two which is presented here.

The Pareto approach is a further step in current research since it proves to be more suitable when it is difficult to combine several objectives into a single aggregated fitness function. More, the cost may be interpreted as a constraint, with the further consequences. A future aspect to be studied is the identification of the most appropriate subset of refactorings that may be applied to each software entity in order to satisfy the nominated objectives.

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