Application of Memetic Algorithms in the Search-based Product Line Architecture Design: An Exploratory Study

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Keywords: Software Product Line, Product Line Architecture Design, Memetic Algorithm.

Abstract: Basic design principles, feature modularization, and SPL extensibility of Product Line Architecture (PLA) design have been optimized by multi-objective genetic algorithms. Until now, memetic algorithms have not been used for PLA design optimization. Considering that memetic algorithms (MA) have achieved better quality solutions than the solutions obtained by genetic algorithms (GA) and that previous study involving the application of design patterns to PLA design optimization returned promising results, bringing the motivation in investigating the use of MA and the Design Pattern Search Operator as local search to the referred context. This work presents an exploratory study aimed to characterize the application of using MA in PLA design optimization. When compared with a GA approach, the results show that MA are promising, since the obtained solutions are slightly better than solutions found by the GA. A pattern application rate was identified in about 30 % of the solutions obtained by MA. However, the qualitative analysis showed that the existing global search operators need to be refactored for the joint use with the MA approach.

1 INTRODUCTION

A Product Line Architecture (PLA) comprises features of a Software Product Line (SPL) (van der Linden and Rommes, 2007), including all possible architectural variations in SPL products. An SPL feature is a system capacity that is important and visible to a user. The PLA is one of the most important artifacts for the SPL success and an analytical study of its design should be considered during the SPL development (OliveiraJr et al., 2013).

The PLA design allows for predicting the quality of an SPL even before constructing it. Therefore, it is possible to perform a structural evaluation using metrics. In addition to metrics, evaluation of a PLA takes into account economic factors, complexity and restrictions on the product, enabling the modeling of the PLA design as a multi-objective optimization problem (Colanzi et al., 2014).

Such considerations have motivated the application of multi-objective search algorithms (MOA) for PLA design optimization. For doing that, it was developed the Multi-Objective Approach for Product-Line Architecture Design (MOA4PLA) (Colanzi et al., 2014), which aims to evaluate and optimize the PLA design regarding basic design principles, feature modularization and SPL extensibility by MOAs.

Memetic algorithms (MA) have been used as an option for optimization algorithm. They are composed of a genetic algorithm (GA) with local search. The concept of search is understood as a kind of optimization, so in the present text, the global search term denotes the optimization performed in a search area covering the entire solution space, while local search concerns the optimization of limited solution space.

MA have allowed better quality solutions than the solutions obtained only by using GA (Fraser et al., 2015; Harman and McMinn, 2010). To the present time, there is no report of using MA for optimizing PLA designs. Although, the use of memetic approach in the context of class modelling (Smith and Simons, 2013) and in other contexts (Chawla et al., 2015; Jeya Mala et al., 2013) showed better results compared to other global search algorithms.

In this sense, the objective of this study is to characterize the application of MA in the search-based PLA design, through an exploratory study, in order to start building a body of knowledge. We are interested in investigating two research questions: ***RQ1***- *"Does memetic algorithm find better quality solutions than the solutions obtained by the global search algorithm in the context of PLA design optimization using MOA4PLA?"* and ***RQ2***- *"Which approach of local search is more effective in the referred context?"*.

Neto, J., Colanzi, T. and Amaral, A.
Application of Memetic Algorithms in the Search-based Product Line Architecture Design: An Exploratory Study.
DOI: 10.5220/0006363201780189
In *Proceedings of the 19th International Conference on Enterprise Information Systems (ICEIS 2017) - Volume 2*, pages 178-189
ISBN: 978-989-758-248-6

In order to obtain evidence to answer both research questions, the exploratory study was divided in three experimental studies. In the first one, experiments involving NSGA-II algorithm with genetic and memetic approaches using PLA designs were performed. The memetic approach uses the Design Pattern Mutation Operator developed in (Guizzo et al., 2014) as local search operator. The results are quantitatively compared in terms of quality multi-objective indicators.

The second experimental study observed the behavior of the local search during the evolution of the MA generations, indicating its effective application in about 30 % of the individuals during the evolutions. Finally, in the third experimental study, a qualitative study was carried out to evaluate the application of the design pattern in the PLA design solutions found and, as a result, it found corrupted pattern applications.

In order to answer to RQ2, the first and third experimental studies involved four different versions of the memetic algorithm based on different types of local search. These versions are explained in Section 3. The experimental results indicate that the version that obtains the best results is also the one that spent less computational cost.

This paper is organized as follows. Section 2 describes MOA4PLA and its automation tool. Section 3 shows how the memetic approach was structured using MOA4PLA. Sections 4 and 5 address the exploratory study definition and threats to validity, respectively. Section 6 presents and discusses the obtained results. Finally, Section 7 concludes the paper and presents future work.

2 PRODUCT-LINE ARCHITECTURE DESIGN

Multi-Objective Approach for Product-Line Architecture Design (MOA4PLA) (Colanzi et al., 2014) is composed of four main activities: (i) Construction of the PLA Representation, (ii) Definition of the Evaluation Model, (iii) Multi-objective Optimization and (iv) Transformation and Selection.

In activity (i) the PLA design is represented by a class diagram including architectural elements, such as: classes, attributes, methods, interfaces and components. It describes the variabilities by means of UML stereotypes and notes. It is encoded as a metamodel instance to be manipulated by the search algorithm. The activity (ii) is responsible for defining an evaluation model consisting of the objectives to be optimized, ie the fitness functions, chosen by the software architect. The current evaluation model includes objective functions to evaluate basic principles of design, feature modularization and SPL extensibility.

The present work used the CM and FM objective functions, the same used in (Guizzo et al., 2014). CM aims to achieve solutions with high cohesion and low coupling, formed by the sum of some conventional metrics (Wust, 2016) as presented in Equation 1, where $DepIn, DepOut, CDepIn, CDepOut$ and $DepPack$ are coupling metrics, $NumOps$ and H are size and cohesion metrics, respectively . FM evaluates the feature modularization of the PLA design being formed by metrics driven to SPL features (Nunes et al., 2009) according to Equation 2.

Activity (iii) receives as input the outputs of activities (i) and (ii) and the constraints used in the optimization process, then at this point, multi-objective search algorithms are used to generate as output the set of solutions which obtained the best trade-off between the objective functions. MOA4PLA allows the use of different multi-objective search algorithms. Finally, the activity (iv) receives the set of solutions generated in activity (iii) and converts each one to a readable model, composed by a class diagram that includes all necessary characteristics for representation.

MOA4PLA defines specific search operators, which are used in the optimization process (activity iii). The six fundamental MOA4PLA mutation operators are: Move Method, Move Attribute, Add Class, Move Operation, Add Manager Package and Feature-Driven Operator (Colanzi et al., 2014). The latter is an operator concerned with feature modularization.

$$CM(pla) = \sum_{i=1}^{c} DepIn + \sum_{i=1}^{c} DepOut + \sum_{i=1}^{cl} CDepIn + \sum_{i=1}^{cl} CDepOut + \frac{\sum_{i=1}^{c} DepPack}{c} + \frac{\sum_{i=1}^{itf} NumOps}{itf} + \frac{1}{\sum_{i=1}^{c} H} \tag{1}$$

$$FM(pla) = \sum_{i=1}^{c} LCC + \sum_{i=1}^{f} CDAC + \sum_{i=1}^{f} CDAI + \sum_{i=1}^{f} CDAO + \sum_{i=1}^{f} CIBC + \sum_{i=1}^{f} IIBC + \sum_{i=1}^{f} OOBC \tag{2}$$

In addition to these operators, the author (Guizzo et al., 2014) proposed a mutation operator to allow the design patterns automatic application in the search-based PLA design, named Design Pattern Mutation Operator. A feasibility analysis showed that three design patterns from the GoF patterns set can be automatically applied: Strategy, Bridge and Mediator. Strategy allows to vary the algorithm independently of its users, therefore, it encapsulates families of algorithms making them interchangeable. Bridge creates an abstraction of its implementation, allowing both to vary independently of each other. Mediator allows a weak coupling avoiding that the objects refer explicitly to each other, for this it creates an object that encapsulates the iterations of an objects set, thus the interactions can vary independently.

The Design Pattern Mutation Operator selects one of these patterns at random. After, it randomly selects a set of classes and interfaces of the PLA design. This set is called scope. Then, if the scope is suitable for applying the selected pattern, the classes and interfaces are changed to accomplish the design pattern.

OPLA-Tool (Optimization for PLA Tool) (Féderle et al., 2015) automates the MOA4PLA application. This tool offers support to all activities of MOA4PLA and also to performing experiments. OPLA-Tool current version implements the NSGA-II (Deb et al., 2002) algorithm, which is based on GA. NSGA-II was used in the present work.

Experimental studies carried out in (Guizzo et al., 2014) identified evidence that the use of Design Pattern Mutation Operator allows better PLA design solutions than the solutions obtained using only fundamental operators. Thus, the next section describes an approach for using the design pattern operator as local search operator in a memetic algorithm.

3 MEMETIC BASED PLA DESIGN

This work proposes the use of Design Pattern Mutation Operator as a local search operator in a memetic approach, integrating global and local search. The motivation for using such an operator is its empirical satisfactory results (Guizzo et al., 2014). As happens in other contexts, we believe that this approach can help to produce better quality PLA design solutions than genetic approach (Chawla et al., 2015; Fraser et al., 2015; Jeya Mala et al., 2013; Smith and Simons, 2013) because a particular design pattern applied in some place of the design could improve some properties of the solution obtained by the global search.

The global search algorithm used is NSGA-II (Deb et al., 2002), a multi-objective variation of GA. From an initial population of individuals (candidate solutions), basic operators are applied to evolve the population, generation by generation. Through the selection operator more copies of those individuals with the best objective function values are selected to be parent. So the best individuals will survive in the next population. The crossover operator combines parts of two parent solutions to create a new one. The mutation operator randomly modifies a solution. The offspring population created from selection, crossover and mutation replaces the parent population.

The memetic algorithm is an extension of GA where is inserted a local search during or after the global search process (Russell and Norvig, 2003). This structure allows the individuals of the global population the possibility of local optimization (Fraser et al., 2015).

Some changes were made in OPLA-Tool for supporting the memetic approach. Fig 1 shows the architecture of OPLA-Tool in which was added the OPLA-Memetic module, responsible for using the Design Pattern Mutation Operator as local search operator.

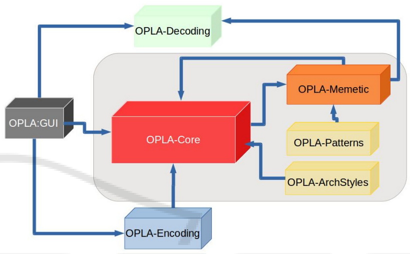


Figure 1: OPLA-Tool Modules.

OPLA-Memetic module follows the same activities of MOA4PLA. However, the main change is that necessarily after the application of a mutation operator, the local search operator is applied whether there is a suitable scope for applying one of the three design patterns implemented in the operator. The pseudocode following presented shows how NSGA-II was adapted to include the local search. Two parents (p_1 and p_2) are selected. The crossover operator obtains two children from the parents. *Children* are mutated and, then, the local search is applied over each child. The *children* resulting from this process follow to a new population.

There are different approaches to select a solution in the local search: First Improvement, Best Improvement and First-Best Improvement. First Improvement (Russell and Norvig, 2003) consists of applying the local search operator once and this solution goes to the next generation regardless of having better or worse quality than the current solution. Best Improvement (Ochoa et al., 2010) goes to the current solution neighborhood and selects the best neighbor. First-Best Improvement is the union of the two previous search approaches.

```
Memetic Algorithmm - Adapted from NSGA-II
 Memetic()
    While EvaluationMax
```

```
    for s = 0 to Population.size/2 Do
      p_1 = Population(s)
      p_2 = Population(s+1)
      children[] = Crossover(p_1,p_2)
      children[1] = Mutation(children[1])
      children[2] = Mutation(children[2])
      children[1] = LocalSearch(children[1])
      children[2] = LocalSearch(children[2])
      NewPopulation = children[1]
      NewPopulation = children[2]
      s += 2
    for end
    Population = Selection(NewPopulation)
  while end
```

Four versions of the local search were implemented to OPLA-Memetic based on the different approaches aforementioned. The first and the second implemented versions are based on the First Improvement approach, with the difference that, in the second version, the best solution from global and local solutions is chosen. The third version uses the Best Improvement approach and the fourth version uses First-Best Improvement. The following subsections present the MA versions implemented.

3.1 MA No Criterion of Choice (NoChoice)

This version of MA uses the First Improvement approach. The MA applies the local search after the application of the global search mutation operator and the current solution proceeds to the next generation in NSGA-II.

```
LocalSearch - NoChoice
   localSearh(solution)
     return s = operatorLocalSearch(solution)
```

3.2 MA Best of 2 (Bestof2)

Bestof2 local search compares the solutions obtained in the global search and in the local search and returns the best one. The following pseudo-code shows this process. Bestof2 saves the original solution in the *sOri* variable. The solution obtained after the local search application is *sLoc*. The two solutions *sOri* and *sLoc* are evaluated and the best one is returned.

The *theBest* solution evaluation method consists of comparing the fitness sums of the global and local search solutions, choosing the solution that has the lowest sum, since an optimization by minimization is performed. A fitness sum consists on the sum of the values obtained for CM and FM objective functions. The *theBest* algorithm is presented in the sequence.

```
LocalSearch - Bestof2
   localSearh(solution)
      sOri = solution
      sLoc = operatorLocalSearch(solution)
      sSelect = theBest(sOri, sLoc)
      return sSelect

TheBest
   theBest(solution1, solution2)
      for f = 0 to ObjectivesNumber do
         sum1 =+ solution1.getFitness(f)
         sum2 =+ solution2.getFitness(f)
      end for
      if (sum2 <= sum1)
         return solution2
      else
         return solution1
```

3.3 MA Best of 12 (Bestof12)

The third version of MA uses the Best Improvement approach, creating a neighborhood of solutions found by local search and returning the best one. The MA was executed in a quad-core processor. Three local searches were instantiated for each core using paging performed by the operational system, what results in 12 neighbors. *theBest* evaluation method is also used to select the best solution of the neighborhood. The Bestof12 algorithm is shown below.

```
LocalSearch  - Bestof12
 localSearh(solution)
   Core0:
      sLoc0 = operatorLocalSearch(solution)
      sLoc1 = operatorLocalSearch(solution)
      sLoc2 = operatorLocalSearch(solution)
   Core1:
      sLoc3 = operatorLocalSearch(solution)
      sLoc4 = operatorLocalSearch(solution)
      sLoc5 = operatorLocalSearch(solution)
   Core2:
      sLoc6 = operatorLocalSearch(solution)
      sLoc7 = operatorLocalSearch(solution)
      sLoc8 = operatorLocalSearch(solution)
   Core3:
      sLoc9 = operatorLocalSearch(solution)
      sLoc10 = operatorLocalSearch(solution)
      sLoc11 = operatorLocalSearch(solution)
   sSelect = theBest12(sLoc0,sLoc1,sLoc2,
   sLoc3,sLoc4,sLoc5,sLoc6,sLoc7,sLoc8,sLoc9,
   sLoc10,sLoc11)
   return (sSelect)
```

3.4 MA First Best Improvement (UntilBest)

The latest version of MA works with the First Best Improvement approach whose pseudo-code is presented below. For doing that, the algorithm repeats the local search over the same global search solution until achieves an improvement in the fitness sum, ie., until finding the first improvement in the neighborhood.

The comparison between the solution found by the global search (*sOri*) and the neighbor (*sLoc*) is performed by the method named *theBestUntil* also presented below. As soon as a better solution is found, the solution *sLoc* is returned. Due to the Design Pattern Mutation Operator needs a suitable scope for applying a design pattern, there are cases where, in spite of a lot of attempts to improve local search, none improvement happens. To prevent this problem, the number of attempts to reach a better solution was limited to fifteen. If there is no improvement, then the solution found by the global search (*sOri*) survives in the next generation.

```
LocalSearch - UntilBest
 localSearch(solution)
    sOri = solution
    best = false
    while (best == false) do
       sLoc = operatorLocalSearch(solution)
       best = theBestUntil(sOri, sLoc)
       count++
       if (count > 15)
          return sOri
    end while
 return sLoc
```

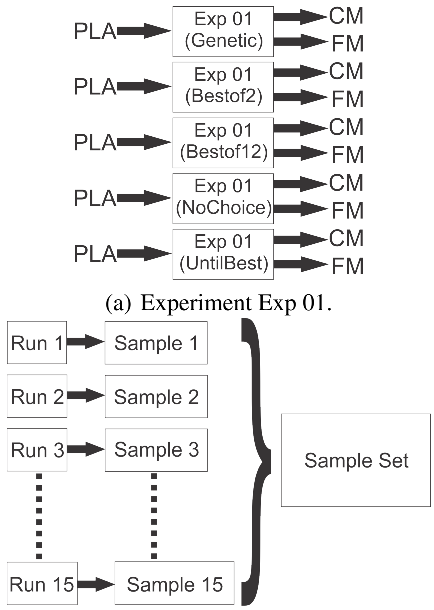
```
TheBestUntil
 theBestUntil(solution1,solution2)
    for f = 0 to ObjectivesNumber do
       sum1 =+ solution1.getFitness(f)
       sum2 =+ solution2.getFitness(f)
    end for
    if (sum2 < sum1)
       return true
    else
       return false
```

4 EMPIRICAL EVALUATION DESCRIPTION

Considering the motivation presented, this section describes the studies carried out to answer the two research questions presented previously. The studies are described below.

This work is composed by three experiments with the objective of evaluating the performance and quality of the solutions found by the memetic approach. The first experiment (Exp 01) used the OPLA-Tool with the following configurations: 15 runs of the NSGA-II algorithm, with all conventional mutation operators using 0.9 of mutation probability, without Crossover. The population size is 100 and the number of fitness evaluation is 30000. The number of fitness evaluations was used as stop criterion for NSGA-II.

Four PLA designs were used in this study. Arcade Game Maker (AGM) is an SPL that includes three



(a) Experiment Exp 01.

(b) Sample Set

Figure 2: Exp 01 and Sample Set.

games: Brickles, Bowling and Pong, developed by SEI (SEI, 2016). Banking System (BANK) is an SPL created by (Gomaa, 2011) for the purpose of managing banking systems. BET (Donegan and Masiero, 2007) is an SPL used to manage urban transport. And, the last SPL used was the Mobile Media (MOM) for media control on mobile devices (Contieri Jr et al., 2011). Information regarding the original fitness, in the format (CM, FM), and the quantity of architectural elements is present in Table 1.

Exp 01 was repeated for each version of the memetic algorithm (NoChoice, Bestof2, Bestof12 and UntilBest) and for Genetic, as can be seen in Figure 2(a) which presents the design of the experiment. In this figure it is possible to observe that the PLA design is one of the independent variables. The other independent variable is the search algorithm version. As dependent variable it was used the fitness of the solutions in terms of the objective functions that were selected as optimization objectives. In this case, CM and FM functions were the objectives (mentioned in Section 2).

Exp 01 was executed 15 times for each independent variable, whose grouped samples form a sample set as can be seen in Figure 2(b). Each experiment in Figure 2(a) used the four PLAs (AGM, BANK, BET and MOM) as an independent variable, one at a time. Thus, there are four sample sets for each algorithm version, each set referring to a PLA, resulting in 20 sample sets.

Those 20 sample sets were evaluated using quality multi-objective indicators and appropriate statistical

Table 1: PLAs Information.

PLA	Original Fitness (CM, FM)	# Components	# Interfaces	# Classes	# Features	# Variabilities
AGM	(89.14, 758.0)	9	14	30	11	5
BANK	(157.0, 326.0)	4	5	25	16	3
MOM	(72.14, 1122.0)	8	15	14	14	7
BET	(461.02, 1486.0)	56	30	115	18	8

analysis, as suggested in (Ferrucci et al., 2013). Five quality indicators were chosen: Hypervolume (HV) (Zitzler et al., 2001), Generational Distance (GD) (Van Veldhuizen and Lamont, 1998), Inverse Generational Distance (IGD) (Radziukynienė and Žilinskas, 2008). Error Ratio (Van Veldhuizen, 1999) and Euclidean Distance from an ideal solution (ED) (Zeleny and Cochrane, 1973).

Some of these quality indicators need the Pareto Front True (PF_{True}), however, in real problems PF_{True} is not known. In these cases, it is common to use the non-dominated solutions found by all algorithms in all runs (Yoo and Harman, 2007; Zitzler et al., 2003). The approximation to the Pareto front is called PF_{known}. Each PF_{known} is formed only by the non-dominated solutions obtained by an algorithm version.

The most accepted indicator for performance assessment of multi-objective algorithms is Hypervolume (HV) (Zitzler et al., 2001). Comparing two PF_{approx} sets: whenever one PF_{approx} completely dominates another PF_{approx}, the HV of the former will be greater than the HV of the latter. The HV indicator calculates the volume in the region enclosed from PF_{approx} to a reference point. A reference point is a point dominated by the solutions of all sets PF_{approx} found. The higher the HV value, the better coverage and the diversity of the solutions set achieved.

The GD indicator (Van Veldhuizen and Lamont, 1998) is used to calculate the distance from an approximation of the Pareto Front found by the algorithm (PF_{known}) to PF_{True}. So, GD is an error measure used to examine the convergence of an algorithm to PF_{True} . IGD (Radziukynienė and Žilinskas, 2008) is an indicator based on GD, but with the goal of evaluating the distance from PF_{True} to PF_{known}, i.e., the inverse of GD.

Error ratio (Van Veldhuizen, 1999) is an error measure to report a finite number of members in PF_{Known} which are not members of PF_{true}. If they are not members of PF_{true} the algorithm has erred or perhaps not converged. Low values of error ratio are better because the lower the error ratio value, the higher the number of solutions of PF_{Known} that are members of PF_{true}.

The last indicator, Euclidean Distance from the Ideal Solution (ED), is not a quality indicator, instead, it is used as a measure to help the decision maker in his/her final decision, i.e., from all solutions provided which one should be selected. ED is used to find the closest solution to the best objectives. An ideal solution has the minimum value of each objective, considering a minimization problem (Zeleny and Cochrane, 1973). These minimum values are obtained from PF_{true} solutions. Thus, the solution with the lowest ED has the best trade-off between the objectives.

The Shapiro Wilk test was used to ascertain whether sample sets are normally distributed. Subsequently, the Friedman Test was used to ascertain whether there was statistical difference between the samples. The two statistical tests were applied with 95 % of confidence ($p - value < 0.05$).

The second experiment (Exp 02) was realized with the purpose of observing the behavior of the application of design patterns, carried out by the local search, during the evolution of MA generations. Exp 02 used the NoChoice version. A single round of the algorithm was performed. The difference is that 10000 fitness evaluations were performed for PLA MOM. Each of the 10000 evaluated solutions was stored, in order to verify the presence of design patterns and thus, to measure the application rate during the generations evolution.

Third experiment, called Exp 03, aimed qualitatively evaluating solutions found by all versions of MA in Exp 01, in order to identify possible design inconsistencies and parts of the design that are suitable to apply design patterns. The solutions considered for this study were those that presented some pattern applied in the PLA design or with the lowest ED for each algorithm version.

5 THREATS TO VALIDITY

This section presents the threats to validity considered in the experiments carried out. The size and diversity of PLAs used in the experiments is a threat because only 4 PLAs were used (only 1 is a real SPL). However, it is difficult to obtain PLA designs available as the level of detail required to conduct experiments. On regards to diversity, PLA designs have different sizes and are from different domains minimizing this risk.

The algorithms are non-deterministic. To mitigate this threat, we performed 15 runs for each experiment. We also used quality indicators, generally used in the multi-objective optimization literature. The adoption of the same population size, the same number of generations independently of the PLA size and the fitness functions CM and FM are other threats. Different configurations of algorithms parameters could imply in different, possibly better, results. We are aware that we should perform other studies involving different PLA designs and different parameters tuning.

6 EMPIRICAL EVALUATION RESULTS AND ANALYSIS

In this section the results obtained in the exploratory study (composed by the three experiments) are presented. In addition to discussing the results, the research questions are answered at the end of the section[1].

6.1 Exp 01

Table 2 shows the amount of solutions which composes the PF_{true} of the Exp 01 as well as the cardinality of the PF_{known} obtained by the algorithms. This table also presents the Error Ratio of each algorithm. The PF_{known} and the Error Ratio are indicated as PF_k and ER, respectively. The lowest Error Ratio value is highlighted in bold. The data of this table indicated that the memetic approach, with the Bestof2 algorithm, found a greater diversity of solutions, since it cover a larger area in the space of solutions, presenting lower Error Ratio in three of the four PLAs used.

The Genetic algorithm version produced identical fitness values in all rounds for PLA BANK. The fitness is CM = 141.5 and FM = 294. Comparing with the original fitness value (CM = 157.0 and FM = 326.0 - Table 1) the optimization is clear. However, the version of the Bestof2 memetic algorithm found a solution that overcomes Genetic with fitness CM = 141.5 and FM = 145, indicating that the solution found by Genetic is not optimal.

Table 3 presents the PLA design solution optimization time in milliseconds. It was expected that the runtime of the memetic algorithm versions would exceed the Genetic algorithm runtime. However, when executing the versions of Bestof12 and UntilBest versions for PLA BET (the largest PLA), it was observed that finishing its executions is impracticable. To perform 30000 evaluations the Bestof12 algorithm would take approximately 10.7 days per round, for 15 rounds 161.5 days, and Untilbest algorithm would take about 22.6 days per round, for 15 rounds would be spent 339.7 days. For this reason, only the samples found in the Genetic, Bestof2 and NoChoice experiments were used for PLA BET.

The Hypervolume quality indicator was applied to the standard samples of Exp 01 involving the Genetic, Bestof2, Bestof12, NoChoice and UntilBest algorithm versions. Table 4 presents the HV indicator average for each algorithm version. The highest average, by PLA, were highlighted in bold, since they represent the version of the algorithm that obtained the best yield. The Bestof2 and Bestof12 versions found better HV averages in all the PLAs used.

Shapiro Wilk statistical test pointed out that the data have a non-normal distribution. The only exception is for the Genetic version sample using PLA BET, whose distribution is normal. Thus, Friedman's nonparametric test was applied to verify the statistical difference between the versions of the algorithms for HV, GD and IGD quality indicators.

As can be observed (last column of Table 4), with 95% of confidence, there is statistical difference between the algorithms for BANK and BET. In this case, the Bestof12 and Bestof2 version of the memetic algorithm obtained the best performance, respectively.

The last column of Table 5 presents the fitness of the ideal solution of each PLA. This fitness was obtained from the PF_{true} of each PLA design used in the study. The other columns of the table present the ED of the solution closest to the ideal solution obtained by the algorithms versions. The lowest ED of each PLA is highlighted in bold. For this indicator, the Bestof2 version stood out getting better values in all four PLAs, and the NoChoice version broke even with Bestof2 in the AGM and BET PLAs. With these results, the Bestof2 version presented the best performance.

Friedman's test showed statistical difference for AGM (p-value = 0.003453), BANK (p-value = 0.03837) and BET (p-value = 0.0366) PLAs. In these three cases, the versions with best performance were: Bestof2 and Bestof12, respectively. In general, it can be stated that the memetic approach equaled or overcame the solutions found by the genetic approach.

The average of the GD quality indicator is presented in Table 6 and the last column shown the p-values obtained by the Friedman test. In this table, it is possible to identify that the Bestof2 version was better in AGM and BET PLAs, and the Bestof12 in BANK and MOM PLAs. However, only BANK and BET PLAs presented p-value < 0.05, with statistical difference,

[1]The experimental package, encompassing PLA designs, quality indicator data, statistical data and the obtained solutions are available at https://github.com/Oplamemetic/experimentalpackage/

Table 2: Number of non-dominated solutions by algorithm.

PLA	#PF$_{true}$	Genetic		Bestof2		Bestof12		NoChoice		UntilBest	
		#PF$_k$	ER	#PF$_k$	ER	#PF$_k$	ER	#PF$_k$	ER	#PF$_k$	ER
AGM	16	12	0.82	12	**0.18**	6	0.80	10	0.67	16	1
BANK	3	1	1	3	**0**	4	0,5	3	1	5	1
MOM	12	7	**0.42**	8	0.62	4	0.75	5	0.6	6	0.66
BET	13	13	0.69	10	**0.2**	—	—	6	0.75	—	—

Table 3: Solution optimization time in milliseconds.

PLA	Bestof2	Bestof12	NoChoice	UntilBest
AGM	161.9	999.5	124.4	1,651.5
BANK	65.3	244.8	34.6	412.0
MOM	197.5	836.4	98.6	1,889.9
BET	2,468.06	31,023.8	2,670	65,223.2

Table 4: Average values of HV.

PLA	Genetic	Bestof2	Bestof12	NoChoice	UntilBest	p-value
AGM	0.200845	**0.227553**	0.213305	0.209683	0.220646	0.28025
BANK	0.108785	0.271241	**0.316004**	0.195562	0.185855	**1.29E-09**
MOM	0.425223	0.437447	**0.447239**	0.382441	0.358863	0.428092
BET	0.223165	**0.245368**	—	0.162444	—	**0.001273**

Table 5: The best ED by Experiment.

PLA	Genetic	Bestof2	Bestof12	NoChoice	UntilBest	Fitness of the Ideal Solution
AGM	268.312601	**51.0**	130.146071	**51.0**	57.428216	(30.14, 256.0)
BANK	149.656272	**14.0**	36.619666	54.083269	36.619666	(127.5, 145.0)
MOM	36.124029	**25.316541**	42.106359	37.0	36.674241	(45.1, 795.0)
BET	762.0	**162.000425**	—	**162.000425**	—	(276.02, 611.0)

where the Bestof2 version surpassed the Genetic one.

The average of IGD quality indicator is presented in the Table 7 and the p-values obtained by the Friedman test are shown in the last column. The Bestof2 version obtained better results in BET, the Bestof12 version in BANK and MOM PLAs, and the UntilBest version in AGM. As in the GD indicator, only BANK and BET PLAs presented p-value < 0.05 indicating statistical difference, where the Bestof2 version surpassed the Genetic one.

The results of Exp 01 show that the memetic approach achieved slightly better fitness solutions than the genetic approach, but in the context of this study the memetic approach is not statistically better than genetic in all cases. One point observed in memetic approach is that it can find a larger number of solutions in PF$_{true}$, which suggests that it explores the solutions space more extensively than the genetic algorithm.

There are indications that the PLA design provided as input may influence the performance of the local search, because the greater number of suitable regions to apply design patterns, the greater the chance of local search to optimize the PLA. By analyzing the PF$_{Knowns}$ of Exp 01 in Genetic, Bestof2, Bestof12, NoChoice and UntilBest versions, no occurrences of patterns were found in any of the non-dominated solutions. This led to another study to investigate whether design patterns were being applied during the optimization process and the rate of pattern application. Results of this study are presented in the next section.

6.2 Exp 02

As mentioned in Section 4, Exp 02 analyzed the rate of application of design patterns in the solutions that comprises each population of 100 generations. The graphs of Figures 3 and 4 show the number of solutions that contained each design pattern, a combination of them, or no applied pattern (due to space limitation only the first and the last generations are presented). Each design pattern, its combination or non-pattern application was represented by a number, as follows: (1) Strategy, (2) Bridge, (3) Mediator, (4) Mediator and Strategy, (5) Strategy and Bridge , (6) Mediator, Bridge and (7) No pattern applied. No solution contained the three design patterns applied.

Analyzing Figure 3 it can be observed that the application of patterns is more present in 40% of the solutions in the 35 first generations. However, with the generations evolution, the rate of patterns application is steadily decreasing to the stage that (Figure 4) approximately $2/3$ of the solutions have no pattern.

Although at least 30% of the solutions have app-

Table 6: Average values of GD.

PLA	Genetic	Bestof2	Bestof12	NoChoice	UntilBest	p-value
AGM	8.262073	**7.328262**	11.001264	7.574039	7.869226	0.5872
BANK	19.104973	7.840005	**6.289115**	17.577093	15.126942	**0.000042**
MOM	11.568652	9.484651	**9.023561**	10.802115	10.253804	0.7113
BET	10.307010	**7.025358**	—	21.678729	—	**0.003698**

Table 7: Average values of IGD.

PLA	Genetic	Bestof2	Bestof12	NoChoice	UntilBest	p-value
AGM	20.675618	19.455419	20.163540	19.708956	**18.790651**	0.2548
BANK	50.718176	43.639684	**39.874537**	44.345701	48.206297	**0.0000036**
MOM	3.781270	4.122948	**3.724295**	4.188424	4.171765	0.297
BET	53.477759	**48.773528**	—	59.169005	—	**0.007699**

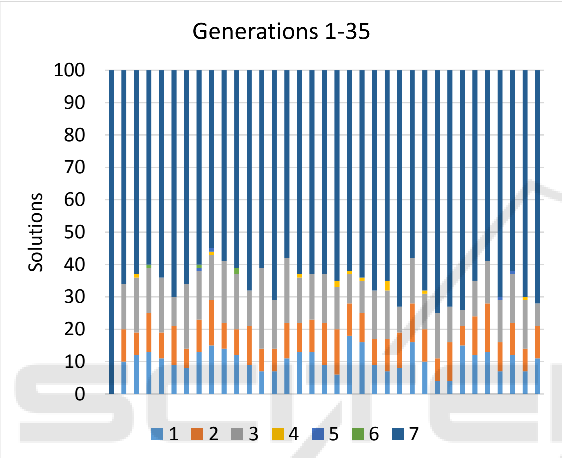


Figure 3: Number of solutions with patterns - 1 to 35 generations.

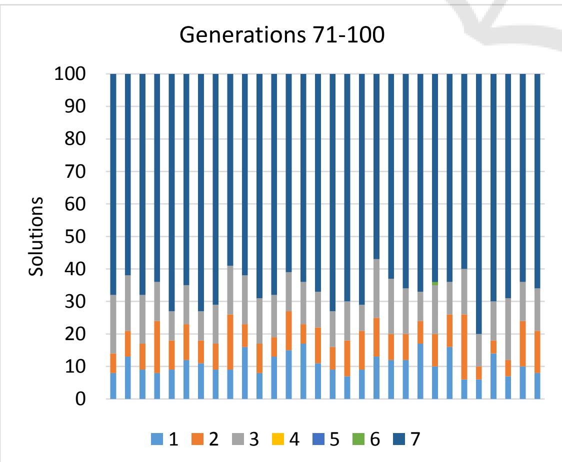


Figure 4: Number of solutions with patterns - 71 to 100 generations.

lied patterns, some have not survived over the generations, since the percentage of application decreases as the process progresses. Still, the surviving solutions are dominated by others and therefore are not part of

Table 8: Patterns Application Rate.

PLA	Number of Solutions	Number of Solutions with Patterns	Application Percentage (%)
AGM	298	6	**2.01**
BANK	140	71	**50.71**
MOM	225	13	**5.77**
BET	202	96	**47.52**

the PF_{Knowns}.

A qualitative study (Exp 03) was developed in order to understand the reasons that lead the discard of solutions with pattern application over the generations, and why the solutions with pattern application were dominated.

6.3 Exp 03

Exp 03 focuses on the PLA solutions found in memetic algorithm versions of Exp 01 (Bestof2, Bestof12, NoChoice and UntilBest) analyzing points where patterns were applied as well as possible inconsistencies in the patterns application. Initially, the solutions with the lowest EDs of each algorithm version were analyzed. Considering the analyzed solutions, only the solution obtained by the NoChoice version for the PLA MOM had the Strategy design applied. All other solutions had no pattern.

Based on this fact, the rate of patterns application in all runs of the algorithm versions was investigated. Table 8 shows the total number of solutions obtained for each PLA in all runs of the algorithms versions in Exp 01. The third column of the table shows the number of solutions that had at least one applied pattern, and the fourth column shows the pattern application percentage. It is noticed an incidence of patterns application in around 50% in the solutions obtained by the algorithms versions in BANK and BET PLAs, and percentages lower than 6% in the other two PLAs (see Table 8).

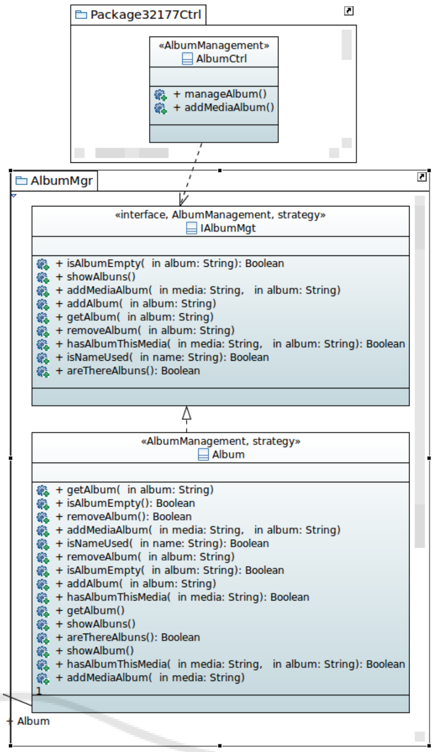
An analysis of the PLAs AGM and MOM, that have the lowest percentage of pattern application, shows that they have at least 1 and at most 3 regions suitable to patterns application. Original designs and solutions that form the PF_{Known} of each algorithm version were analyzed. However, as local search randomly selects the set of classes and interfaces that will have its application scope analyzed, there is no guarantee that the algorithm will specifically find the suitable scope to the design pattern application.

For BANK and BET, which had the highest rates of pattern application, some solutions that have pattern were randomly selected because the solutions of PF_{Known} did not contain patterns. BANK solutions contained only the Strategy pattern, and BET solutions presented the Strategy and Mediator patterns.

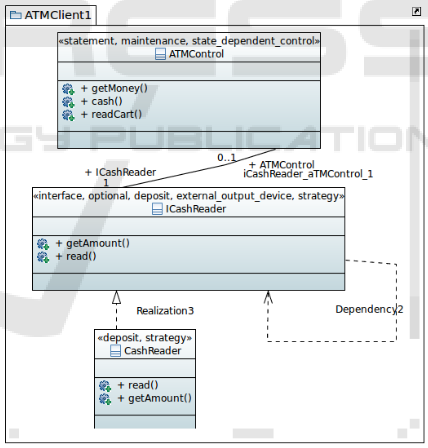
Analyzing MOM solution obtained by NoChoice version containing the Strategy pattern in BET and BANK solutions, it was detected that there is inconsistency in pattern application. An excerpt of the MOM solution obtained by NoChoice version is shown in Figure 5(a). In this solution, the application of the Strategy pattern appears in two classes. *IAlbumMgt* interface represents the Strategy interface, and *Album* class is a member of the algorithm family that implements the Strategy Interface. Besides, *AlbumCtrl* class has a dependency relationship with the Strategy Interface. Although the application presents all the architectural artifacts necessary for the Strategy pattern, the algorithm family contains one member, unlike the behavior of the local search operator that only applies Strategy if there are at least two members to characterize a family. Thus, it is possible to conclude that the application of the pattern is corrupted.

Figure 5(b) presents two architectural elements in which Strategy is applied in a BANK solution (Bestof2 version). The *ICashReader* Interface represents the Strategy Interface and the *CashReader* class represents the algorithm family that implements the Strategy Interface. However, the algorithm family does not have at least two members, the ATMControl class has no dependency relationship with the Interface, and the dependency self-relationship in the *ICashReader* interface represents inconsistencies for this pattern.

In all analyzed solutions it was possible to identify that the applied design pattern is incomplete. The validation tests of the operator's implementation in the context of local search did not detected such a bug probably because the tests was executed lower number of generations than the experiment. Our hypothesis is that inconsistencies are caused by modifications made by global search operators that corrupt the pattern over the generations, because they have not been prepared to do not change design-pattern regions.



(a) Exp 01 NoChoice MOM.



(b) Exp 01 Bestof2 BANK.

Figure 5: Solutions Excerpts with Incomplete Applied Design Patterns.

As results presented in study Exp 02 it is understood that during the generations, there are individuals that have some scope of pattern application, in about 30%. Nevertheless, global search operators causes changes in the application of design patterns, creating damage to the structure of the PLA (producing an incomplete design pattern), which consequently undermines the fitness values of the objective functions what causes the elimination of the solution during the search process.

6.4 Answering the Research Questions

The research questions presented in this paper are answered in this section. The answer to ***RQ1***-*"Does memetic algorithm find better quality solutions than the solutions obtained by the global search algorithm in the context of PLA design optimization using MOA4PLA?"* is that in Exp 01, there was no significant decrease in the solutions fitness of memetic approach, however, there is a slight improvement. This can be seen in Figures 6(a) and 6(b) which show the PF_{true} and PF_{knowns} of each algorithm version for AGM and BANK. It is possible to see that PF_{knowns} are similar, but the front achieved by Bestof2 version is nearer to PF_{true} than the other fronts, confirming the quality indicators results.

It is also noticed that the memetic approach obtained greater diversity of solutions exploring the solutions space in a different way. Studies Exp 02 and Exp 03 have provided clues that global search mutation operators may be harming the results of the memetic approach.

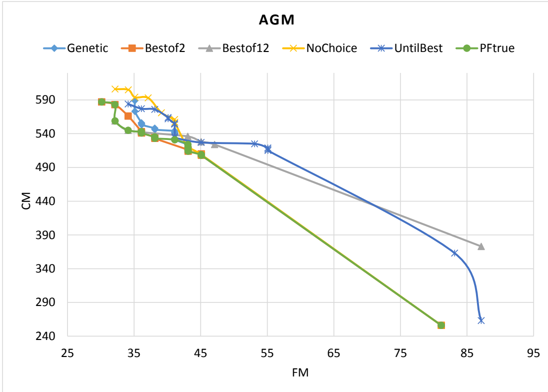
Based on this evidence, the hypothesis that the memetic algorithm is able to find solutions of better quality than the genetic algorithm in the context of search-based PLA design can be maintained. To investigate this hypothesis, it is necessary to refine the global search operators and repeat the experiments.

RQ2 *is about "Which kind of local search is more effective in the referred context?"*. To answer this question an analysis was performed on the results found in the quality indicators of Exp 01. This analysis counted how many times each algorithm version had the best performance in the five quality indicators. Bestof2 version presented better results (with 12 best performance), the Bestof12 version (with 6 best performance) came in second and the other algorithms have the best best at most 1 time.

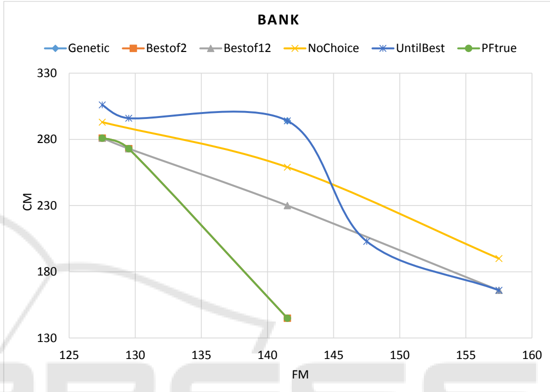
Thus, local search using First Improvement approach which maintains, in the next generation, the best solution among the solutions achieved by global and local search was more effective in the context of PLA design optimization.

7 CONCLUDING REMARKS

This work presented an exploratory study, subdivided into three experimental studies, aiming to characterize the application of memetic algorithms in the search-based PLA design. The memetic approach found greater diversity of solutions showing that it is able to explore the solutions space differently from the genetic approach. A memetic algorithm version obtained



(a) PF_{true} AGM



(b) PF_{true} BANK

Figure 6: PF_{true} AGM and PF_{true} BANK.

the best results in several cases, despite of it was not statistically better than genetic.

In addition, patterns have been substantially applied, although the solutions with patterns do not appear among the non-dominated solutions returned by the algorithms. In one of the experiments, a probable cause was: the global search mutation operators modify the architectural elements that contain applied design patterns since there are no restrictions implemented to prevent this.

A work in progress consists of implementing these constraints on mutation operators to inhibit the alteration of architectural elements presenting design patterns and the repetition of all experiments. As future work, we intend to use other objective functions directly related to the changes caused by the design patterns in the optimized PLAs. There is also a need for a qualitative study to evaluate the solutions found by genetic and memetic approaches from the point of view of software architects.

ACKNOWLEDGEMENTS

The authors thank to CNPq and CAPES for financial support.

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