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Challenges of Multi-Objective Optimization in Feature Model of Software Product Line

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Abstract— **Development of specific product with high reusability of existing resources, Software Product Line (SPL) is vastly used. Feature model is used to maintain the features of SPL in systematic way with common and variable features. Variable features differentiate the products of SPL domain. Optimization is required to find all possible combination of features for specific product under constraints and requirement of stakeholder. Multiple requirements and objectives from stakeholder make it hard to select best feature selection. Different multi-objective optimization algorithms are used in industry to get best optimized feature selection from feature model. In this paper we identify challenges and issues after systematic review of popular algorithms and their optimized results in large and small scale feature models.**

Keywords- Software Product Line, Feature Model, Multi-objective optimization, Optimal feature selection.

I. INTRODUCTION

Software Product line is widely used in software industry for development of products from existing resources. In SPL domain, common and variable features are exist which are used for application development. SPL is more sophisticated approach for product derivation with improvements in cost, productivity, quality and time to market by reusability of common resources whereas variable components differentiate products of SPL under specific requirements of stakeholder [1].

Feature model is roadmap to construct different products of SPL to manage the common and variable resources. New product is developed by configuring suitable features according to stakeholder requirements. Feature model is tree structure of features which comprises with multiple constraints among features. Most common constraints or relationship among features are alternative, optional and mandatory. Cross-tree constraints indicate non-hierarchical contains mutual dependency, OR, and XOR relationships which increase the complexity of feature model. Valid set of feature selection for specific product under the requirements of stakeholder is only if no constraint violation is occurred which is defined in feature model. Optimized feature selection is best approach to select set of features combination under given cross-tree constraints and user requirement constraints [2].

Optimization in feature model is desirable when stakeholder select features for specific functional requirements and quality attributes. Efficient feature selection is hard when number of requirements or objectives getting high. In multi-objective optimization more than one solution feature sets are configured which make difficult to select one of them for product derivation. To find required configuration space, conflicting objectives (lower cast, lower memory consumption and higher performance) effect on solution space quality. Pareto-front is used to indicate solution space for multi-objective optimization. Product developers make trade-off between conflicting multi-objectives in pareto-front solution space [3].

Multi-Objective Evolutionary Algorithms (MOEA) are used for optimization in feature model to find possible solution set of features for specific product derivation. MOEA generate pareto-front solution space when more than one objectives from stakeholder [4]. Non-dominated Sorting Genetic algorithm (NSGA) and Indicator Based Evolutionary Algorithm (IBEA) is widely used in research industry of SPL feature model for multi-objective optimization. High constraints in large feature model, it is very hard to find high quality pareto-front solutions. In large feature model where number of variable are in thousands and n objectives from stakeholder, it is complex to assign the correct attribute values to each feature in feature model and increase probability of constraint violation.

In this paper we discuss about challenges and issues for multi-objective optimization in feature model of SPL. We did systematic review of previous research and compared the results of different MOEA according to stakeholder requirements and pareto-front solutions correctness.

Rest of this paper is organized as follows. Section II discusses feature model background, section III provides information of multi-objective optimization of feature model, section IV describes challenges of MOEAs in feature model and, section V gives conclusion.

II. FEATURE MODELING BACKGROUND

Feature model is organized as a tree structure with hierarchy of parents and nodes. Each node has parent except root node. Feature model exist on alternative, optional and mandatory features. Relationships of mutual exclusion and mutual dependencies are used to present constraints in feature model (Kang et al.). Configuration of new product is derived by combining terminal features. Figure 1 shows a Database (DB) feature model [4].

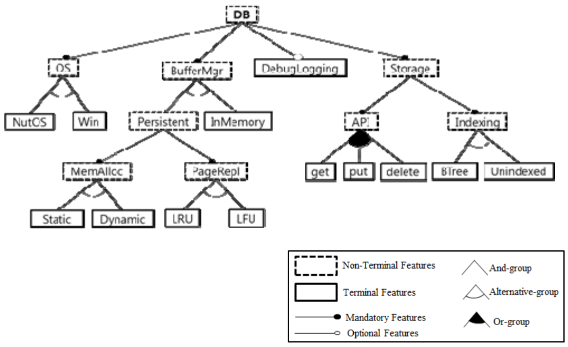

Figure 1. Feature Model of a Database

III. MULTI-OBJECTIVE OPTIMIZATION OF FEATURE MODEL

Stakeholder sort out features from feature model to drive a specific product which satisfies the desired functionality according to requirements and quality attributes. Features consist on n functional properties and attributes which make it hard to choose desired features of stakeholder. Furthermore, the constraint complexity of feature model makes it hard to optimize solution for specific product derivation in SPL. Desired configurations make conflict to choose best multi-objective optimized solution, and to overcome such conflict, developers need to trade-off between features selection [5].

A. *Pareto-Front of Feature model Optimization*

In multi-objective optimization problems, multiple solutions exist which satisfy different multiple objectives simultaneously. Minimizing cost, minimizing storage memory and maximize performance is multi-objective problem which is hard to get on single solution where all objectives satisfy. Optimal solutions require trade-off between conflicting objectives. A solution is non-dominated in pareto-front if no any other solution is degrading it [5].

IV. CHALLENGES OF MOEAS IN FEATURE MODEL

For multi-objective optimization in feature model, three MOEAs i.e., NSGA, IBEA and Strength SPEA, are mostly used in recent research due to high performance and high accuracy of feature selection for configuration of product. These algorithms follow the most steps of Genetic Algorithm such as crossover on single point, bit flip mutation, binary competition for selection next generation. Difference between these algorithms is fitness assignment value which is used to find the stronger individuals.

Multi-objective optimization is performed on E-Shop feature model by using above discussed MOEAs with low and high parameters, every feature with 3 attribute values: Defects, Cost and Used Before. Three Quality attributes considered in this study to measure the pareto-front solutions are, 1) Hypervolume (HV): calculate the space size covered by pareto-front solutions, 2) Spread: measure spread extent in optimized solution, 3) %correct: calculate the percentage of correct solution [6]. From given results, selection of features for specific product of E-Shop does not achieve complete requirement configurations of stakeholder. Numbers of challenges from previous research are discussed below.

Challenge 1: Correctness of configured features solution set.

Challenge 2: Maximum range of multiple objectives of MOEA and maximum number of features in feature model to get correct solution set.

TABLE I. MOEAs on E-Shop Feature Model [6]

MOEA	Parameters	HyperVolume (HV)	%Correct
IBEA	Low	0.293	66.8%
	High	0.271	9.9%
NSGA	Low	0.192	2.4%
	High	0.211	0.6%
SPEA	Low	0.204	0.8%
	High	0.174	0.0%

From results, with high and low parameters IBEA performs best than NSGA and Strength Pareto Evolutionary Algorithm (SPEA). However, these approaches perform well only with 1 or 2 objective functions. Therefore, increase in the number of objective effect on quality of optimization [6].

Table 1, IBEA performed multi-objective optimization with 66.8% correct mean value which clearly indicates that the requirement of multi-objective does not fully met. SPEA correctness value is 0.0% but the hypervolume is 0.174, therefore the violation occurred in complete configuration solution set.

TABLE II. MOEA on LVAT Feature Models [7]

Feature Model	Total Features	Total Rules	NSGA-II		IBEA	
			%Correct	HyperVolume (HV)	%Correct	HyperVolume (HV)
Linux X86	6888	343944	0%	0	0%	0.021
uClinux	1850	2468	3.3%	0.16	31%	0.30
Fiasco	1638	5228	2%	0.18	100%	0.20
FreeBSD	1396	62183	0.5%	0.024	98%	0.34
eCos	1244	3146	2%	0.082	100%	0.33
axTLS	684	2155	3.3%	0.21	100%	0.21
ToyBox	544	1020	12.5%	0.21	25%	0.22

In [7], as given results of multi-objective optimization with IBEA and NSGA-II, big difference of correct features selection for specific product not completely fulfill requirements of end user. Challenges and problems from correctness of features selection with IBEA and NSGA-II are discussed below.

Challenge 3: Identifying criteria where violation of rules is occurred?

In FreeBSD large number of rules (constraints) are 62,183, due to this it is difficult to find exact place where rules violation occurred.

Challenge 4: How to minimize constraint violation in complex and large feature model?

Table 2, shows the result of NSGA-II and IBEA are used for multi-objective optimization in LVAT feature models (Linux X86, uClinux, Fiasco, FreeBSD, eCos, axLTS and ToyBox). Optimization is performed with feature fixing and without feature fixing in feature model. But we discuss here the results of %correct and hypervolume with feature fixing because of best result output. IBEA performed 100% correct feature selection i.e. the requirement of stakeholder for configuration of specific product derivation is fully meet.

However, for Linux x86 feature model the correctness is 0% and FreeBSD the value of %correct is 98% which indicate rules violation in optimized feature selection. IBEA performed best according to results but violation of rules makes it ambiguous for specific product derivation. In FreeBSD, total number of features are 1,396 and rules are 62,183.

V. Conclusion

Optimization in feature model is required for developing specific product under stakeholder requirements. Derived product is correct only if it meets all objectives and functionality of stakeholder. In this paper we done systematic review of research and found challenges related to multi-objective optimization of feature model. We reviewed different MOEAs which are mostly used for multi-objective optimization of feature model and perform critical analysis on output solution. IBEA performs best to achieve comparatively correct solution set features than other MOEAs. In future we will overcome these challenges with some techniques and methods.

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