Optimized Feature Selection for Initial Launch in Dynamic Software Product Lines

Ismayle de Sousa Santos[1], Evilasio Costa Junior[1,*], Rossana Maria de Castro Andrade[1,†], Pedro de Alcântara dos Santos Neto[2,‡], Leonardo Sampaio Rocha[3,§], Claudia Maria Lima Werner[4,¶] and Jerffeson Texeira de Souza[3]

[1]*Department of Computer Science, Federal University of Ceará, Fortaleza, Brazil*

[2]*Department of Computer Science, Federal University of Piauí, Teresina, Brazil*

[3]*Science and Tecnology Center, State University of Ceará, Fortaleza, Brazil*

[4]*Computer Systems Engineering Program, Federal University of Rio de Janeiro, Rio de Janeiro, Brazil*

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Abstract: A Dynamic Software Product Line (DSPL) allows the generation of products that can adapt dynamically according to changes in requirements or environment at runtime. This runtime adaptation is often made by the activation and deactivation of features, introducing a cost (e.g., an overhead regarding resource consumption). To reduce this cost, a solution is the partial product configuration at the static binding time. Thus, in DSPLs, one challenge is the feature selection to define which features should be bound permanently before the initial launch and which features should be bound at runtime. In this paper, we address this challenge presenting a graph model formulation to the feature selection problem for the initial launch in DSPLs that considers both static and dynamic binding. This model allows the application of efficient optimization algorithms to solve the problem. We also present a proof of concept showing that the model can be used to generate optimized solutions to the feature selection problem for initial launch in DSPLs.

1 INTRODUCTION

A Software Product Line (SPL) is a reuse-oriented approach that aims the development of products by reusing common artifacts (Eriksson and Hagglunds, 2003). Despite the benefits of an SPL, it cannot handle the dynamic variations (at runtime) in user requirements and product environment (Hallsteinsen et al., 2008). To address this gap, Dynamic Software Product Lines (DSPLs) emerged as an extension of the concept of conventional SPLs, enabling the generation of software variants at runtime (Bencomo et al., 2012).

In order to support dynamic variability, a DSPL has *multiple and dynamic binding* (Capilla et al., 2014). The binding time is the time at which one decides to include or exclude a feature from a product (Chakravarthy et al., 2008). According to Rosenmüller et al. (Rosenmüller et al., 2011), the static binding occurs when a feature is bound in a program before load time (e.g., at compilation time), whereas the dynamic binding occurs at load time or after loading a program. In traditional SPL engineering, features are bound only statically. Thus, once the product is generated from the SPL, it cannot longer be changed at runtime (Hallsteinsen et al., 2008). DSPLs, however, can combine static and dynamic binding and, therefore, their features can be bound several times and at different time periods (Capilla et al., 2014).

Thus, DSPLs can produce software capable of adapting to user needs and evolving resource constraints (Hallsteinsen et al., 2008). It is worth noting that the static binding provides fine-grained customization without any influence on the resource consumption, but it can result in a *functional overhead* when features included in the product are not used (Rosenmüller et al., 2009). Dynamic binding, in turn, provides more adaptability by dynamically

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loading features when required, but usually, introduces an overhead regarding resource consumption and performance, and increases the execution time (Rosenmüller et al., 2011)(Rosenmüller et al., 2009). Therefore, one partial DSPL product configuration, binding some of the variation points at design time, can be done before the initial launch for dealing with the trade-off between the advantages and disadvantages of each binding time.

In this scenario, the product configuration problem is how to decide which features should be bound only statically, before initial launch, and which features should be bound dynamically.

In a small SPL, it is feasible to use exact techniques to solve the product configuration problem based on feature attributes (Olaechea et al., 2014). These attributes specify extra-functional information such as speed or RAM required to support the feature (Benavides et al., 2010). Meanwhile, in a medium or large SPL, this solution can take a prohibitive time. Then, the use of Search Based Software Engineering (SBSE), which refers to the use of computational search as a mean of optimizing software engineering problems (Harman et al., 2014), can be necessary to obtain an optimum solution in an acceptable time. In fact, we agree with Lopez-Herrejon et al. (Lopez-Herrejon et al., 2015) that "the product configuration naturally lends itself to the application of SBSE techniques because of the vast number of combinations that SPL requirements can typically have".

After an analysis of the literature (see Section 6), we observed that the existing approaches did not address the feature selection problem in DSPLs, before the initial launch. Addressing this gap, this paper proposes a multi-objective approach based on a graph model for the feature model rules verification. We decide to use a graph approach, because it can facilitate the representation and understanding of the feature model rules, besides allowing the use of different optimization algorithms to solve the feature selection problem. Moreover, this approach is easily implementable, once that graphs are well-known structures. There is already some SBSE approaches that model the feature selection problem using graphs (Wang and Peng, 2014), but they are focused in SPL.

The main contributions of this paper are as follows:

- we present a graph model created from the features model considering both static and dynamic binding times. Any optimization algorithm can be used with the proposed model to solve the feature selection problem for the initial launch in dynamic software product lines; and
- we introduce a multi-objective generic formulation for the feature selection problem in a DSPL; and
- we present a proof of concept performed to assess the feasibility of using our proposal to generate optimum solutions to the feature selection problem for initial launch in DSPLs;

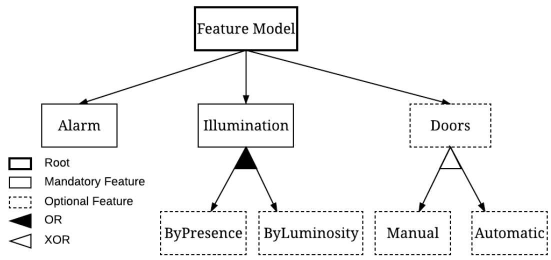


Figure 1: An example of SPL feature model.

2 FEATURE MODEL

Features are attributes of a system that directly affect end-users (Kang et al., 1990). In a feature model, the features are presented in a hierarchical way, and the basic rules are: (i) the root feature is included in all products; (ii) a child feature can only be included in a product if its parent feature is included; and (iii) a variation point is a point in the feature model where a choice needs to be made. Figure 1 shows an example of SPL feature model, where the features *Illumination* and *Doors* are variation points.

Usually, a feature model allows the following relationships among features (Benavides et al., 2010):

(i) *Mandatory*, a child feature has a mandatory relationship with its parent when the child is added in all products in which its parent feature appears;

(ii) *Optional*, a child feature has an optional relationship with its parent when the child can be optionally added in all products in which its parent feature appears;

(iii) *Xor*, a set of child features has a Xor-relationship with its parent when only one child feature can be selected when its parent feature appears; and

(iv) *Or*, a set of child features has an Or-relationship with its parent when one or more of them can be included in the products in which its parent feature appears.

A feature model can also contain cross-tree constraints specified by *require* and *exclude* relationships between features (Benavides et al., 2010). In an SPL, if a feature *A excludes* a feature *B*, then both features cannot be included in the same product. If a feature *A requires* a feature *B*, then there is a dependence relationship where if feature *A* is included in a product, then feature *B* is also included.

It is worth noting that in a DSPL, a variation point can be bind at runtime by (de)activating the features. In this scenario, if a feature *A excludes* a feature *B*, then these features cannot be active in the product at the same time. Also, if a feature *A requires* a feature *B*, then the activation of the feature *A* enforce the activation of the feature *B*.

Futhermore, some feature model notations, as the Odyssey-FEX (Fernandes et al., 2011), consider that a model can have feature groups. In an SPL, feature groups are variation points, where there are a minimum and a maximum number of features that must be added to the product. In a DSPL, feature groups specify the minimum and maximum numbers of features in the group that can be active in the product at the same time.

Lastly, an SPL/DSPL product is a selection of features of the feature model. To be a valid product configuration, this selection should satisfy all feature model rules and relationships.

3 FEATURE SELECTION PROBLEM IN DSPL

According to (Capilla et al., 2014), a DSPL has the following properties:

- **P1**: *Runtime Variability Support*. A DSPL must support the activation and deactivation of features and changes in the structural variability that can be managed at runtime;
- **P2**: *Multiple and Dynamic Binding*. In a DSPL, features can be bound several times and at different time periods (e.g., from deployment to runtime); and
- **P3**: *Context-Awareness*. DSPLs must handle context-aware properties that are used as input data to change the values of system variants dynamically and to select new system options depending on the conditions of the environment.

In the next paragraphs, we depict the relationship between the DSPL properties presented by Capilla et al. (Capilla et al., 2014) with the feature selection problem for the initial launch.

Because of property **P1**, to *maximize the dynamicity* (reconfiguration possibilities at runtime) is an important objective that should be considered in the DSPL feature selection problem. The DSPL dynamicity is correlated with the number of features that can be activated or deactivated at runtime. Thus, this optimization objective is necessary due to the goal of a DSPL that is to generate products, which can be dynamically configured according to changes in the requirements or environment.

As a consequence of property **P2**, the *binding type* (static or dynamic) is an essential attribute that has to be considered in the DSPL feature selection problem for the initial launch. The more features are left to dynamic binding, the more the product is adaptable at runtime. On the other hand, the more features are bound dynamically, the more the product will be complex. The complexity occurs because the dynamicity requires a binder for selecting the values of the variants at runtime (Capilla et al., 2014). Besides, the dynamic binding usually has a cost of performance and memory consumption (Rosenmüller et al., 2011). Therefore, the static binding has an important role in the DSPL scenario to derive a configuration for the initial launch following the resource constraints related to the reconfiguration process. This binding reduces the effort for computing a configuration of a DSPL by minimizing the number of dynamically bound modules. Some authors call a DSPL that deals with both time periods as Hybrid DSPL (Bencomo et al., 2012), where some variation points are bound only statically, and others are left open for rebinding at runtime.

The property **P3** affects the features activation and deactivation at runtime. For this reason, this property is not addressed in the feature selection problem for the initial launch, which is discussed in this paper.

3.1 Motivating Example

As a motivating example consider the problem of feature selection in the DSPL called Mobile Guide (Marinho et al., 2013) [6], which is related to the development of mobile and context-aware tour guides. Figure 2 presents a small part of the Mobile Guide feature model in the Odyssey-FEX notation (Fernandes et al., 2011). One of its products is the GREat Tour (Marinho et al., 2013) that is a tour guide in the GREat[7] laboratory at the Federal University of Ceará.

In Figure 2, we have one variation point (*Show Documents*) that can be bound at runtime. This variation point is related to the document types (text, image, and video) shown to the visitor. The type of document is available according to the battery charge level. If the charge level is low, then only texts are available. If the charge level is medium, then the visitor can access texts and images. Lastly, if the battery

[6] http://mobiline.great.ufc.br/index.php
[7] http://great.ufc.br

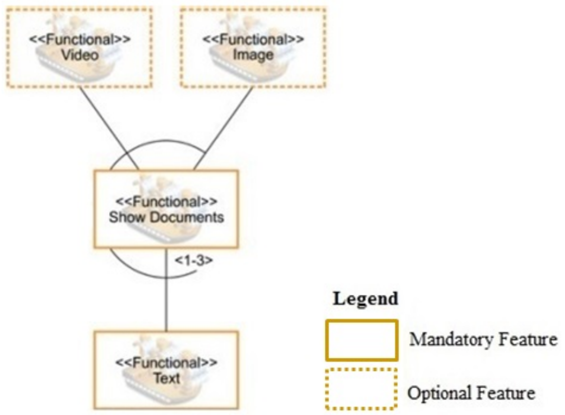


Figure 2: A variation point of the Mobile Guide feature model (Marinho et al., 2013).

charge level is high, all document types are available. Low, medium and high values are defined empirically before the application is deployed.

As "Text" is a mandatory feature, it has to be always active. However, as regards to the other two features of the variation point *Show Documents*, the following question arises in the product configuration for the initial launch: *Should we bind the features "Video" and "Image" permanently at static binding time or should we leave them to be bound dynamically (at runtime) according to the changes in the battery charge level?*. Thus, in our example, we have four options: (i) only static binding for both features; (ii) dynamic binding for both features; (iii) only static binding for the feature "Video" and dynamic binding for the feature "Image"; and (iv) only static binding for the feature "Image" and dynamic binding for the feature "Video".

By applying only the static binding, we affect the dynamicity of the product, but this can be necessary to satisfy the resource constraints (e.g., time spent in the activation/deactivation of features). Then, to answer the question aforementioned, we need feature attributes related to the binding time to decide the best option to satisfy both the customer and the resource constraints. Depending on the attributes values, for a given customer, for example, it can be more interesting to remove the feature "Video" permanently (static binding) and leave only the feature "Image" to be bound at runtime (dynamic binding).

Therefore, the problem is to derive a partial product configuration from a DSPL, with the maximum adaptability (the main goal of a DSPL), maximum value to the customer (to satisfy him/her), and minimum cost (to optimize the resources), respecting the feature model rules (to be a valid product).

4 A GRAPH MODEL FORMULATION FOR FEATURE SELECTION IN DSPL

In this section, we describe our graph model, the problem objectives of our formulation and the feasibility rules.

4.1 A Graph Model

In our formulation, from the feature model, we generate a directed graph for the verification of the rules of this model and the identification of feasible solutions to the feature selection problem in a DSPL.

The graph $G = (V, E)$ represents the features and the relationships between features defined by feature model rules. Each vertex $x \in V$ corresponds to a feature of the model. The vertices are divided into two sets that indicate if the feature is optional or mandatory.

$$V = V_m \cup V_o$$

where

$$Vm = \{\ \text{x} \in V_m\ |\text{x is a mandatory feature}\}$$

$$Vo = \{\ \text{x} \in V_o\ |\text{x is a optional feature}\}$$

In order to define the graph edges, three concepts are used: *feature dependency, feature proximity, and statically exclusion*. When a feature x depends on a feature y, it means that the feature x requires y. The proximity of a feature x is the set of features so that x requires at least one of the features in its proximity. If a feature x excludes statically a feature y, then both x and y cannot be activated simultaneously in the product.

Thus, the set of edges E is divided into three subsets, where each subset denotes an edge type.

$$E = E_d \cup Ev \cup E_e$$

where

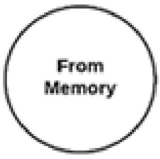
$$Ed = \{\ \text{xy} \in E_d\ |\text{x depends on y}\}$$

$$Ev = \{\ \text{xy} \in E_v\ |\text{y belongs to the proximity of x}\}$$

$$Ee = \{\ \text{xy} \in E_e\ |\text{x excludes statically y}\}$$

Table 1 shows how the vertices and edges are represented in the graph. Mandatory features (set V_m) generate filled vertices. Optional features (set V_o) generate unfilled vertices. Edges from the set E_d are represented by continuous arcs. Edges from the set E_v are represented by dotted arcs. Lastly, edges from the set E_e are represented by dashed arcs.

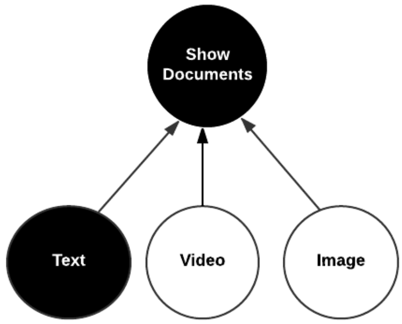
Table 1: Graph Components.

Components	Type or Relationship
	Optional
	Mandatory
	Dependency
	Proximity
	Exclusion

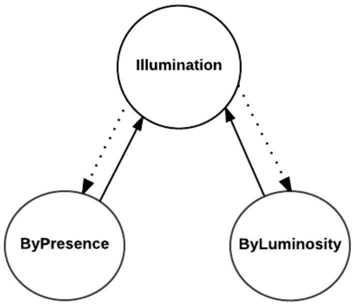
A feature model may have also a set of feature groups (FG). Each group g has a minimum ($minFG(g)$) and maximum ($maxFG(g)$) quantity of features that may be active at the same time in the product. In the graph, there are no specific components to represent the feature groups, but they can be added during the implementation of the graph data structure, as exemplified in our proof of concept (see Section 5).

Figure 3 shows the relationships among the features in the graph. Figure 3.a shows an example of father and son relationship. In this figure, the features “Text”, “Video” and “Image” can only be selected, if “Show Documents” was selected. In Figure 3.b, an example of require relationship with the operator *Or* is presented. In this case, if the feature “Illumination” is selected, it requires that at least one feature from the set [“ByPresence”, “ByLuminosity”] is selected.

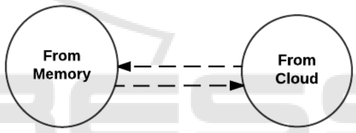
Figure 3.c shows an exclude relationship, where if a feature in this relationship is activated, the other cannot be activated at the same time. Then, if a feature is related to others by dashed edges, and this feature is selected for the product as static, the others cannot be selected to the product. Lastly, Figure 3.d shows a require relationship using the operator *Xor*. In the latter, if the feature “Doors” is selected, it requires that at least one among the features “Manual” and “Automatic” is selected. Moreover, if a feature among the features “Manual” and “Automatic” is selected at static time to be always active, the other feature cannot be selected.



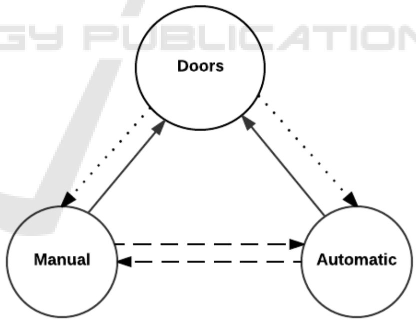
(a) father and son dependence



(b) require with the operator *Or*



(c) exclude



(d) require with the operator *Xor*

Figure 3: Feature model relationships represented in the graph.

4.2 Problem Objectives

In our problem formulation, presented bellow, a solution F_p is composed by a subset of features of the feature model selected for the product. The dynamicity of the DSPL products can be improved by maximizing the number of features with dynamic binding (1). Moreover, to better satisfy the user, we should maximize the value ($value(f_n)$) (2) of the features selected (f_n), which can be measured through feature attributes like utility or quality attributes (even those related to the context awareness). Despite limiting the feasible solutions to a resource constraint, we suggest to use an objective to minimize the cost ($cost(f_n)$) of the features (3). This cost can be, for example, regarding performance, resource usage, or monetary value. Thus, the results of the optimization process with a multi-objective algorithm show a set of options with different costs that the customer may choose. As we discussed in the previous sections, since the DSPL features can be bound statically or dynamically, we consider two kinds of costs: i) *CostD*, which is the feature cost when it is left to the dynamic bind; and ii) *CostE*, which is the feature cost when it is bound only statically.

$$\text{Maximize} \sum_{f_n \in F_p} dynamicity(f_n) \tag{1}$$

$$\text{Maximize} \sum_{f_n \in F_p} value(f_n) \tag{2}$$

$$\text{Minimize} \sum_{f_n \in F_p} cost(f_n) \tag{3}$$

where

$$dynamicity(f_n) = \begin{cases} 1, & \text{if } f_n \text{ is selected with bound dynamically} \\ 0, & \text{if } f_n \text{ is selected with bound only statically} \end{cases}$$

$$cost(f_n) = \begin{cases} costD, & \text{if dynamicity}(f_n) = 1 \\ costE, & \text{if dynamicity}(f_n) = 0 \end{cases}$$

4.3 Feasibility Rules

In our formulation, a solution is feasible only if it respects the following constraint:

$$brokenFeasibilityRules(F_p) = 0 \tag{4}$$

It means that all feasibility rules, i.e., the feature model rules (see Section 4.3.2), should be satisfied by the solution.

4.3.1 Vertex Value

Each vertex x, related to a feature, has an integer $s(x)$, that indicates the state of the feature. The possible values to $s(x)$ are:

$$s(x) = \begin{cases} \text{0, if feature x was not selected} \\ \text{1, if feature x was selected as static} \\ \text{2, if feature x was selected as dynamic} \end{cases}$$

We can also define $num_1(g)$ and $num_2(g)$ as the number of features in a group g selected as static and dynamic, respectively. Then, $num_1(g) = |\{x \in g \mid s(x) = 1\}|$ and $num_2(g) = |\{x \in g \mid s(x) = 2\}|$.

4.3.2 Rules

A solution is feasible if the following rules are satisfied:

1. If $x \in V_m$, then $s(x) = 1$
   - If the feature is mandatory, it must be selected at static time;
2. If $x, y \in V$ and $xy \in E_d$, then if $s(x) \neq 0$, then $s(y) \neq 0$
   - If a feature x depends on a feature y, feature x can just be selected if y is also selected;
3. If $x \in V$ and $Y \subset V$, such that $Y = \{y \in Y \mid y \neq x$ and $xy \in E_v\}$, then if $s(x) \neq 0$, then $\sum_{y \in Y} s(y) > 0$
   - If a set of features Y belongs to the proximity of a feature x, then feature x can only be selected, if at least one of the features in set Y is also selected;
4. If $x, y \in V$ and $xy \in Ee$, then if $s(x) = 1$, then $s(y) = 0$
   - If a feature x excludes a feature y, and the feature x is selected as static, then feature y cannot be selected;
5. $\forall g \in FG, \sum num_1(g) \leq maxFG(g)$
   - The solution cannot select more static features belonging to the same group than the maximum number of active features allowed at the same time in that group;
6. $\forall g \in FG, \sum num_1(g)) + \sum num_2(g) \geq minFG(g)$
   - The number of selected features belonging to a group, independently of if static or dynamic, must be greater than or equal to the minimum number of features that may be active at the same time in that feature group;
7. $\sum_{f_n \in F_p} cost(f_n) \leq maxCost$
   - The cost of the solution should be less than *maxCost*, which is a maximum cost that the customer is willing to spend;

Rule 1 is used to check if the feature is mandatory. Rules 2 to 4 validate the relations depicted in Figure 3. Rules 5 and 6 are used to validate the feature groups rules. Lastly, rule 7 limits the cost of the product.

5 PROOF OF CONCEPT

A proof of concept was performed to verify the feasibility of using the graph model and the formulation proposed for solving the feature selection problem in a DSPL. In our proof of concept, we used three feature models: (i) Mobiline, discussed in Section 3.1; (ii) a DSPL for smart homes, called SmartHome (Carvalho et al., 2017); and (iii) one artificially generated feature model.

We used the framework JMetal (Durillo and Nebro, 2011) to run the proof of concept with the algorithm NSGAII (Deb et al., 2002a) and IBEA (Sayyad et al., 2013b). These algorithms were selected, because they are used in several related work that deal with feature selection (Pascual et al., 2013a)(Sayyad et al., 2013a).

5.1 Population Representation

We represent a DSPL feature model with "n" features through two strings S1 and S2 of "n" binary digits. In S1, the value "1" for a digit indicates that the feature is selected ("0" for unselected feature). In S2, the value "1" for a digit indicates that the feature should be bound dynamically, while "0" means that the feature should be bound only statically. For example, Table 2 shows the representation of two products with both strings S1 and S2. In Product 1, the feature "Video" was not selected (its corresponding bit in S1 = 0), and, in this case, it does not matter its value in S2 (could be 0 or 1). Besides, in Product 1, the feature "Image" is selected, but at the static binding time (its corresponding bit in S2 = 0), meaning that it is always active. In Product 2, both features "Image" and "Video" are selected (bit in S1 = 1) and left to be bound at runtime (bit in S2 = 1).

Table 2: Example of product representation.

Product	Feature	bit of S1	bit of S2
Product 1	Image	1	0
	Video	0	0/1
Product 2	Image	1	1
	Video	1	1

In relation to the features states presented in Section 4.3.1, when the value s(x), associated to the feature represented by the vertex x in the graph, is 0, it means that S1 = 0. When S1 = 1 and S2 = 0, we have s(x) = 1. And when S1 = 1 and S2 = 1, we have s(x) = 2.

5.1.1 Feature Models Setting

Henceforward, we call the feature model from the Mobiline project (Marinho et al., 2013) as Mob, the model of SmartHome as Sma, and the artificial feature model as 200D. To generate the artificial DSPL feature model, we used a procedure based on the method of Thum et al. (Thum et al., 2009) to randomly create a feature model.

Table 3 presents an overview of the feature models used in the experiments. In this table, we show the number of features and rules of the models used.

Table 3: Feature models used in the experiment.

Model	N. of features	N. rules
Mob	33	24
Sma	17	19
200D	200	128

5.1.2 Feature Values and Costs

The value of a feature indicates their relevance to the customer and can be defined by the Requirement Analyst according to the requirements provided by the customer. In our proof of concept, we consider that the value of a feature can vary from 0 to 5 according to their level of relevance to the customer, where:

$$value = \begin{cases} 0\text{, if the feature is irrelevant} \\ 1\text{, if the feature is very little relevant} \\ 2\text{, if the feature is somewhat relevant} \\ 3\text{, if the feature is moderately relevant} \\ 4\text{, if the feature is very relevant} \\ 5\text{, if the feature is extremely relevant} \end{cases}$$

In an SPL or DSPL, the cost of a feature must be defined by the development team, because it is related to the cost of generating and modifying the assets (e.g., code elements) which will compose the features (Cruz et al., 2013) (Santos Neto et al., 2016). We suggest the following formulas to calculate the costs of the feature in static (costE) and dynamic (costD) binding:

$$costE = costIN + costBA + costCF \text{ and}$$

$$costD = costIN + costBA + costCF + costAD$$

where

- costIN is the inherent cost of using the feature, which includes the value of use of the feature and its assets that were created during the DSPL engineering process;
- costBA is the average cost of energy consumption of the feature in the deploy environment;
- costCF is the cost of customizing feature assets for the product;
- costAD is the cost of the insertion of the runtime adaptation logic; this cost is related to the context-awareness of DSPLs;

We also consider that each of these costs can assume a value between 0 and 5 according to the level of complexity of the task associated (costIN, costCF, costAD) or energy consumption (costBA), where:

$$cost = \begin{cases} 0, \text{if it does not exists} \\ 1, \text{if it is too low} \\ 2, \text{if it is low} \\ 3, \text{if it is moderate} \\ 4, \text{if it is high} \\ 5, \text{if it is too high} \end{cases}$$

The level of complexity, mentioned before, involves not only the difficulty of carrying out the task but also the time spent on it and the impact on the product.

The values and costs for Mobiline and SmartHome models were generated artificially following the above-mentioned ranges. To obtain the real costs, it is needed to survey the customers and developers of this DSPLs, but this was out of the scope of this work. For the artificial DSPL, the costs and values were also generated randomly.

5.1.3 Setting Up the Algorithm

In the algorithms used in the proof of concept, we applied the following parameters: Population Size of 100, Crossover (Single-Point Crossover) Probability of 0.9 and Mutation (Bit-Flip Mutation) Probability of 0.05. Besides, for the feature models (Mob, Sma, 200D), we ran the algorithms with 200k evaluations. In all cases, each algorithm run was repeated 30 times for ensuring more reliability.

5.1.4 The Graph

In our proof of concept, the graph is represented as an object. Besides, we use the adjacent list concept for its representation. In practice, a vector of `Vertex` objects was created, where each `Vertex` contains a list of edges, which have this vertex as origin, and a color (black or white), to verify whether the feature related to the vertex is mandatory or not. Each edge is represented by a tuple that indicates the destiny vertex of the edge and a type (continuous, dotted or dashed), to denote to which set of edges (see Section 4.1) it belongs. Lastly, the `GraphModel` object also has a second list containing the features groups.

5.2 Execution Flow

Figure 4 shows the flowchart of the execution of our proof of concept. The process started when the feature model was used as input to our flow. Next, the graph is generated, and the multi-objective optimization algorithm was configured. Once the configurations are done, we executed the optimization algorithm. During the execution of each loop of the optimization algorithm, the graph was used to validate solutions.

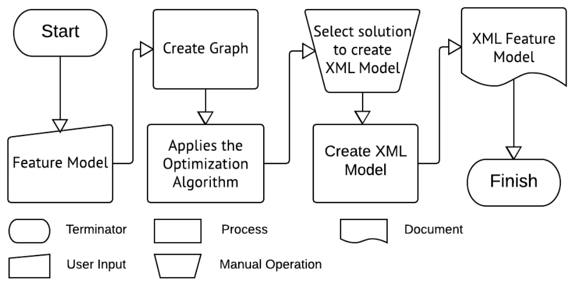


Figure 4: Proof of Concept flowchart.

At the end of the execution of the algorithm, the best valid solutions were identified. We can consider the best solutions like the one with the highest dynamicity, the lowest cost, the best value, or those solutions that are closest to the Pareto front, such as, we can use measures like SPREAD (Deb et al., 2002b) and Hypervolume (HV) (Zitzler and Thiele, 1999). Table 4 presents the average of the number of correct solutions, solution values, solution costs, number of dynamic features, HV and SPREAD. These values were generated by the optimization algorithms using Mob, Sma and 200D models considering a maximum cost equals to 400 for the first two models and 700 for the last one. Table 5 presents three feasible solutions for SMA model after running the optimization algorithm NSGAII. This data can be used to assistant the choose of the most appropriate solution for the product of the DSPL.

Lastly, the DSPL Requirement Analyst selects the solution from which a feature model will be generated to be used by the development team. In our proof of concept, for each valid solution selected, an XML file following a pattern similar to the one used by the Software Product Line Online Tools (S.P.L.O.T)(Mendonca et al., 2009) can be generated as output. Figure 5 presents an example of the generated XML file, and the corresponding features, from the Solution 1 presented in Table 5.

5.3 Discussion

This proof of concept shows initial evidence that our model can be used to provide an optimized way to solve the feature selection problem for the initial launch in DSPL. Our model allows the use of different optimization algorithms to check and generate optimal solutions.

Regarding Table 4, it is possible to verify a large

Table 4: Results of the executions of the optimization algorithms.

Alg	Mod	Correctness	Value	Cost	D. Feat.	SPREAD	HV
NSGA	Mob	34.86 ± 3.7	52 ± 1.7	290.49 ± 8.34	14.5 ± 0.5	0.70 ± 0.03	0.41 ± 0.004
	Sma	50.16 ± 2.0	59 ± 0.6	173.42 ± 2.18	4.5 ± 0.5	0.91 ± 0.03	0.40 ± 0.002
	200D	18 ± 6.4	233 ± 17	497.40 ± 41.87	28.5 ± 3.5	0.66 ± 0.04	0.34 ± 0.008
IBEA	Mob	2.6 ± 1.47	64.4 ± 1.8	375.05 ± 10.88	22.23 ± 0.6	0.64 ± 0.02	0.47 ± 0.003
	Sma	44.3 ± 1.23	62.6 ± 0.1	196.82 ± 0.91	7 ± 0	0.97 ± 0.02	0.42 ± 0.001
	200D	65.5 ± 6.1	307.7 ± 6.5	557.18 ± 13.31	40.7 ± 1.5	0.57 ± 0.03	0.47 ± 0.007

Table 5: Example of solutions for Smart Home (Sma) DSPL.

	Variable 1	Variable 2	Value	Cost	D. Feat.
Solution 1	11111010011101010	00100100000101010	44.0	128.0	5
Solution 2	11111010011111010	00000000000101000	49.0	128.0	2
Solution 3	11111010011111010	00000100000100010	49.0	132.0	3

variation of the results obtained by the algorithms used. This variation came from the implementation of the algorithms. In a nutshell, it is possible to realize that the NSGA algorithm generated on average solutions with lower costs, but the IBEA algorithm generated on average solutions with better values and more dynamic features. We believe that the small number of correct solutions generated by the IBEA algorithm for the Mobiline features model is a result of the maximum cost that was overcome by the majority of the solutions generated by the IBEA. In the other models, this does not occur. In these models, it is possible to note that the average cost was considerably lower than the maximum cost established. Finally, the small amount of correct solutions obtained by the NSGA algorithm for the 200D model corroborates with what was stated in (Sayyad et al., 2013b), that indicated the NSGA algorithm tends to deteriorate rapidly.

We emphasize that the detailed comparison of the results generated by the optimization algorithms goes beyond the scope of this paper. Thus, it is important to highlight that the goal of this proof of concept was not to present the best solution regarding the model implementation or the best optimization algorithm to solve the problem of the selection of features in DSPLs.

In addition, the difficulty to obtain real Dynamic Software Product Lines, as cited also in (Bezerra et al., 2016), makes it difficult to evaluate the optimization model for the feature selection problem in the real environment. Lastly, the study of the best algorithms to solve the presented problem is left as future work.

5.4 Threats to Validity

One threat to the validity of the results is the use of synthetic data as attributes of features, i.e., values, cost and the DSPL generated artificially. We produce these data artificially due to the difficulty of obtaining real DSPL data. The generation of synthetic data has also been used by other authors in experiments with search-based algorithms (Sayyad et al., 2013b)(Guo et al., 2011).

It is important to emphasize that there is not a precise way to define the feature cost since it depends on the implementation of the product. In (Cruz et al., 2013) and (Santos Neto et al., 2016) are presented estimation approaches for generating this cost, but this forecast depends on the information of the assets related to each feature, and measures correlated to them. For example, these approaches use the number of lines of code and coupling of an asset.

Another threat to validity is related to the Pareto Front generated from the JMetal (i.e., without using a brute force search algorithm to find the real Pareto Front). This can have impacted the results of the evaluations, because it may not be the best solution. Besides, the way with the structure of the graph was implemented affects both time and correctness rate and, therefore, more experiments are required to measure the impact of this implementation on the objectives optimized.

6 RELATED WORK

We identified in the literature related work to the feature selection problem in a SPL (Guo et al., 2011)(lin Wang and wei Pang, 2014)(Sayyad et al., 2013b)(Henard et al., 2015) and in a DSPL (Pascual et al., 2013b; Pascual et al., 2015)(Pascual et al., 2013a)(Sanchez et al., 2013).

Guo et al. (Guo et al., 2011) and Wang and Pang (lin Wang and wei Pang, 2014) present approaches mono-objective for SPL feature selection. Guo et al. (Guo et al., 2011) use Genetic Algorithm to find an optimized feature selection that minimizes or max-

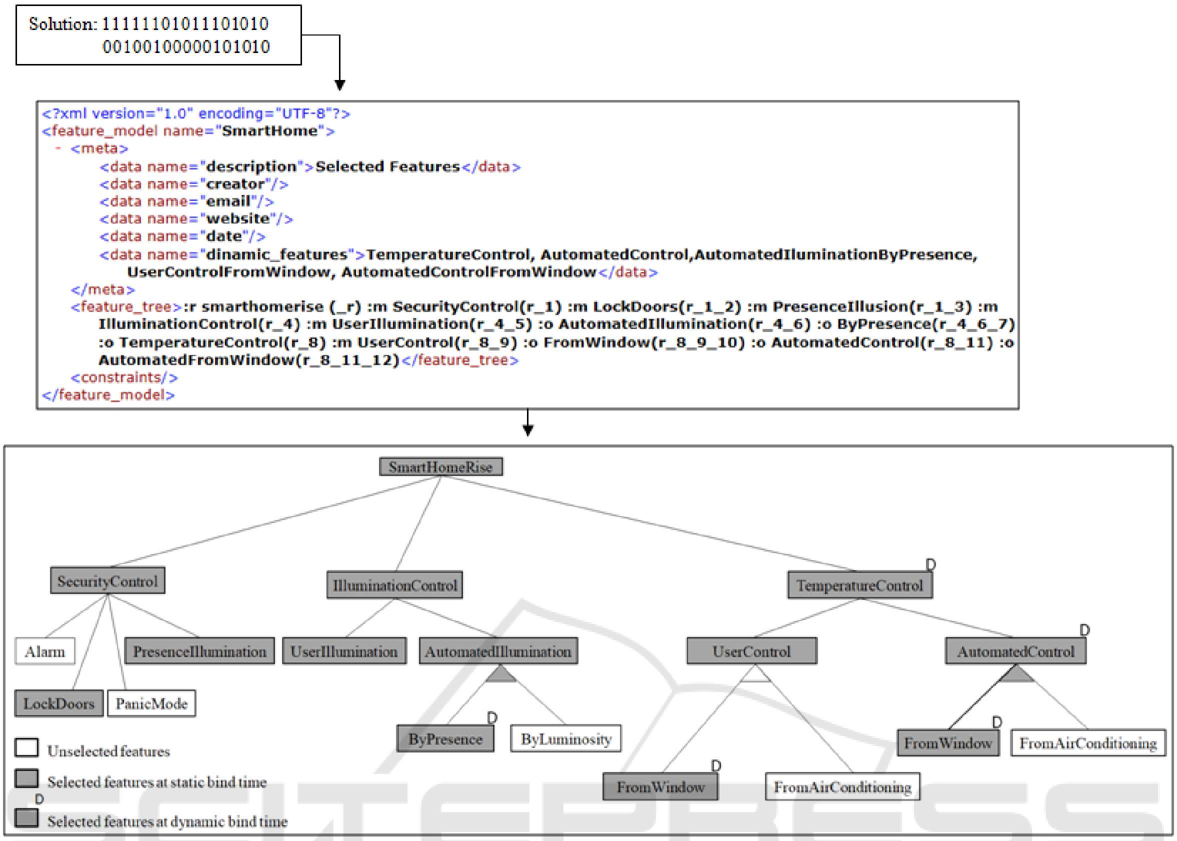


Figure 5: Example of solution for the SmartHome DSPL.

imizes an objective function. Wang and Pang (lin Wang and wei Pang, 2014) uses a graph to represent a feature model and an ant colony optimization to get a solution to the SPL feature selection optimization problem that maximizes the product value subject to constraints.

Sayyad et al. (Sayyad et al., 2013b) compare the results of seven multi-objective evolutionary optimization algorithms using up to five optimization objectives. Christopher et al. (Henard et al., 2015) propose SATIBEA, an approach for configuring massive SPLs with over five thousand features using an approach that blends an optimization by merging the IBEA algorithm and a model validation using SAT solver.

In the DSPL scenario, Pascual et al. (Pascual et al., 2013b; Pascual et al., 2013a; Pascual et al., 2015) describe an approach for the automatic runtime generation of application configurations and reconfiguration plans in a DSPL. The goal of this approach is to choose the architectural configuration, using a genetic algorithm, which provides the best functionality, while not exceeding the available resources (e.g., memory) at runtime. Sanchez et al. (Sanchez et al., 2013) propose an algorithm for selecting at runtime the configuration that optimizes given quality metrics. The goal of this approach is to determine the arrangement most suitable, especially concerning the following non-functional aspects: quality of service, performance, and reconfiguration time.

As described in the previous paragraphs, we identified work related to the feature selection problem in SPL (Guo et al., 2011)(Wang and Peng, 2014) (Sayyad et al., 2013b) (Henard et al., 2015) and some work dealing with the feature selection problem in a DSPL at runtime (Pascual et al., 2013b) (Pascual et al., 2013a) (Pascual et al., 2015) (Sanchez et al., 2013).

The studies focused on SPL do not address runtime adaptation, and then, they do not take into account the dynamic binding time. The latter, addressing DSPLs, were worried with the optimization of the resources used (Pascual et al., 2013a)(Pascual et al., 2013b)(Pascual et al., 2015) or of quality metrics at runtime (Sanchez et al., 2013). Thus, these studies do not support the decision of which features should be bound statically and which one should be bound dynamically.

We also find in the literature related work (White et al., 2014) (Lochau et al., 2017) that considers the multi-step configuration problem to DSPL, that involves transitioning from a starting configuration through a series of intermediate configurations to a configuration that meets a desired set of end state requirements. However, these studies do not aim to achieve a feature optimized configuration. Thus, the difference of our work is that our proposed graph model can solve the feature selection problem in DSPL's by indicating a optium solution and considering both the static and dynamic binding time.

7 CONCLUSIONS

In a typical SPL, the feature selection is made statically only, whereas in a DSPL we also have the dynamic binding to provide product adaptation at runtime. This runtime adaptation introduces a cost that can be reduced by defining a partial product configuration for initial launch.

We proposed a graph model and a multi-objective formulation that considers both static and dynamic binding time to help in the decision of which features should be bound permanently at static binding time and which features should be bound at the dynamic binding time. Our model allows the use of different techniques to check and generate the optimal solutions.

We also presented a proof of concept that shows the feasibility of using our model to obtain optimized feature model configurations, indicating if the features should have to be bound at the static or dynamic time. With this information, the Requirement Analyst has a set of feasible submodels (i.e., DSPL products) to be offered to the customer.

As future work, it can be verified other ways to implement the graph structure and the best way to calculate the cost of dynamic feature (costD) and static feature (costE). Also, experiments can be performed to assess what is the best multi-objective optimization algorithm to be used for our proposed formulation. Moreover, it would be interesting to investigate if the proposed graph could be adapted to check a feasibility of the features model at runtime when there is a change in the product.

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