Automated Planning for Feature Model Configuration based on Functional and Non-Functional Requirements

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ABSTRACT
Feature modeling is one of the main techniques used in Software Product Line Engineering to manage the variability within the products of a family. Concrete products of the family can be generated through a *configuration* process. The configuration process selects and/or removes features from the feature model according to the stakeholders' requirements. Selecting the right set of features for one product from amongst all of the available features in the feature model is a complex task because: 1) the multiplicity of stakeholders' functional requirements; 2) the positive or negative impact of features on non-functional properties; and 3) the stakeholders' preferences w.r.t. the desirable non-functional properties of the final product. Many configurations techniques have already been proposed to facilitate automated product derivation. However, most of the current proposals are not designed to consider stakeholders' preferences and constraints especially with regard to non-functional properties. We address the software product line configuration problem and propose a framework, which employs an artificial intelligence planning technique to automatically select suitable features that satisfy both the stakeholders' functional and non-functional preferences and constraints. We also provide tooling support to facilitate the use of our framework. Our experiments show that despite the complexity involved with the simultaneous consideration of both functional and non-functional properties our configuration technique is scalable.

Categories and Subject Descriptors
D.2.13 [**Software Engineering**]: Reusable Software – *Domain engineering and Reuse models.*

Keywords
Software Product Line Engineering, Feature Model, Configuration, Artificial Intelligence, Planning Techniques.

1. Introduction
Software Product Line Engineering (SPLE) aims at developing a set of software systems that share common features and satisfy the requirements of a specific domain [1]. A technique adopted in SPLE for managing reusability is *commonality* and *variability modeling* through which common assets and their variability are formalized. A software product line lifecycle encompasses a *domain engineering* process and an *application engineering* process. In the domain engineering process, a comprehensive formal representation of the products of the domain is developed. This includes a variability model and core assets of the product family. *Feature models* are among the prevalent variability modeling techniques in SPLE and represent variability in terms of differences between the features of the products that belong to the software family. A *feature* is "a logical unit of behavior specified by a set of functional and non-functional requirements" [2].

On the other hand, the application engineering process is responsible for capturing target application requirements, deriving a concrete product from the variability model through a *configuration process*, and deploying the product into the users' environment [3]. Using feature models as variability modeling tools, the configuration process selects a suitable set of features to satisfy the stakeholders' requirements. Selecting the best set of features based on the stakeholders' needs is a complicated process because:

1. Features may have either positive or negative impact on the different business concerns of a product, and hence expose different quality attributes. We refer to business concerns of a product (e.g., security and customer satisfaction) and its quality attributes (e.g., performance and cost) as non-functional properties (NFPs), where a non-functional property is defined as: "A property, or quality, that the product must have, such as an appearance, or a speed or accuracy property" [9]. For example, a feature may have a negative impact on *security*, but a positive impact on *customer satisfaction* or it could have high *performance* but low *reliability*.
2. In addition to functional requirements, stakeholders may have several constraints and preferences over non-functional properties in the product derivation. For example, one stakeholder may ask for a product with *high security, high customer satisfaction,* and *cost* less than $1000; and can mention that the *customer satisfaction* is more important than *security.*

The need for considering these additional requirements regarding non-functional properties and preferences over non-functional properties (point 2 above) leads to the increased complexity of the configuration process. Various configuration techniques and tools have been developed to help reduce the complexity of the configuration task by automating some steps of it. A few existing techniques allow for the configuration of feature models based on both functional and non-functional requirements [20][25]. Some techniques have addressed this problem by transforming the feature model configuration problem into a Constraints Satisfaction Problem (CSP), and have used CSP-solvers to build optimal configurations [20][26]. The main problem with these techniques is time inefficiency. Other techniques solve this problem by applying approximation algorithms, but their final configurations are only partially optimal [25]. To our knowledge, almost all these works except [18] only support limited types of NFPs (i.e., quantitative NFPs such as footprint and cost) and do not consider qualitative NFPs (e.g., security). Moreover, no work has considered the preferences of stakeholders in terms of the relative importance between non-functional properties in the process of feature model configuration; and relative importance varies depending on the stakeholders' standpoint and application domain [6]. Relative importance of non-functional properties is especially important for the stakeholders and software designers who are able to define the relative importance among the available functional and non-functional op-

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tions but have difficulty in deterministically picking their choice from those options [6]. Thus, a product line configuration technique should not only be able to operate over deterministic functional choices, but should also be able to operate given the relative importance between both functional and non-functional properties.

The above issues motivated us to address the following research question: How can a product be automatically derived from a feature model in such a way that it satisfies stakeholders' requested functionality and at the same time optimizes their preferences and requirements over the non-functional properties?

To address this research question, we look into preference-based planning techniques. Various preference-based planning techniques exist that produce a plan by optimizing a set of given preferences [4][28]. Hierarchical Task Network (HTN) planning is a popular planning technique, which is suited for domains with hierarchical task decomposition [28][15]. The HTN Planning technique generates plans from a developed hierarchal network of domain tasks and actions [4]. That is, having modeled tasks, actions, and their constraints in the HTN formalism, HTN planners produce a sequence of actions that perform some given tasks. Recently, requirements engineering research has employed planning techniques for preference-driven goal-oriented requirements engineering. Their reported results have shown the suitability of planning techniques for similar structures [29]. By way of analogy between the feature model configuration process and the HTN planning problem, we are motivated to investigate the applicability of HTN planning for the product line configuration problem. Hence, we hypothesize that HTN planning can form the basis for a configuration technique that can answer our research question.

We propose and develop a framework, similar to [18], which extends feature models with annotations reflecting different non-functional properties. We then use HTN planning [4][5] to select a set of features which: 1) satisfy the stakeholders' functional requirements; and 2) optimize the non-functional requirements and preferences of the stakeholders. In comparison to existing configuration approaches, our approach has the benefit of not only satisfying the structural and syntactic constraints of feature models during the configuration process, but also taking both qualitative and quantitative NFPs as well as the relative importance over NFPs into account. In our proposed approach, the configuration problem is converted into an HTN planning problem and planning techniques are utilized to solve the problem [5]. SHOP2 [5], an HTN-based planning system widely used for planning problems, is employed to identify an optimal plan.

In the context of feature model configuration, the main contributions of this paper are as follows:

- We introduce an easy-to-understand formalism for capturing the stakeholders' preferences over non-functional properties represented in terms of relative importance;
- We produce an optimal feature model configuration, by transforming a feature model and stakeholder preferences into a planning problem by considering both functional and non-functional requirements.

This paper is organized as follows: Section 2 introduces feature modeling, non-functional properties, and the HTN formalism. Next, in Section 3, the configuration problem is formally defined and a utility function is developed based on non-functional requirements and preferences. Section 4 introduces the transformation rules for converting a feature model into the HTN formalism. Implementation aspects and tooling are explained in Section 5, which is followed with a comprehensive evaluation and analysis given in Section 6. Section 7 systematically compares our approach with related works and Section 8 concludes the paper and outlines the future work.

2. Foundation

2.1 Feature Models

In SPLE, a feature model is used mainly for representing variability between products. A feature model provides a formal and graphical representation of the variability relations, constraints, and dependencies of the product lines' features. It has a tree-like structure [8] in which features are typically classified as: *mandatory*–a feature must be included in the description of its parent feature in each configuration of the feature model; *optional*–a feature may or may not be included in its parent description in a configuration of the feature model; *alternative feature group*–one and only one of the features from a feature group can be included in the parent description in a configuration of the feature model; *or feature group*–one or more features from a feature group can be included in the description of the parent feature in a configuration of the feature model. Additionally, a number of relations are defined to represent mutual interdependencies (also referred to as *integrity constraints*) between features. The two most widely used integrity constraints are [8]: *requires*–the presence of a given (set of) feature(s) requires the inclusion of another (set of) feature(s); and *excludes*–the presence of a given (set of) feature(s) requires the exclusion of another (set of) feature(s).

Feature models address commonality through *core features* – mandatory features whose parents are mandatory as well. A feature model can be formally defined as follows:

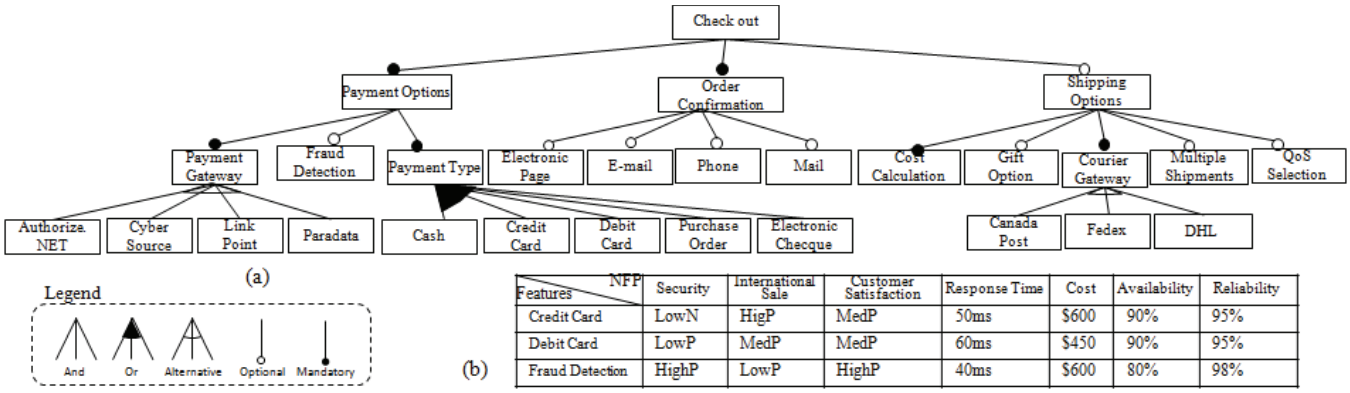
Definition 1 (Feature model). A feature model is a sextuple FM = $(\mathcal{F}, \mathcal{F}_O, \mathcal{F}_M, \mathcal{F}_{IOR}, \mathcal{F}_{XOR}, \mathcal{F}_{ic})$ where 1) $\mathcal{F}$ is a set of features; 2) $\mathcal{F}_O \subseteq \mathcal{F} \times \mathcal{F}$ is a set of parent and optional child feature pairs; 3) $\mathcal{F}_M \subseteq \mathcal{F} \times \mathcal{F}$ is a set of parent and mandatory child feature pairs; 4) $\mathcal{F}_{IOR} \subseteq \mathcal{F} \times \mathcal{P}(\mathcal{F})$ and $\mathcal{F}_{XOR} \subseteq \mathcal{F} \times \mathcal{P}(\mathcal{F})$ are sets of pairs of child features and their common parent feature grouping the child features into optional and alternative groups, respectively; 5) $\mathcal{F}_{ic} \subseteq \mathcal{F} \times \mathcal{F}$ is a set of integrity constraint s (i.e., requires or excludes).

Figure 1 depicts a Check out feature model – a part of the online shopping feature model [7].

2.2 Non-Functional Requirements and Properties

According to a commonly referenced definition [12], non-functional requirements describe the properties, characteristics or constraints that a software product must exhibit. Non-functional properties of software can then encompass aspects like development constraints, business concerns, or external interfaces.

We assume that non-functional properties can be specified in either a qualitative form or a quantitative form. The qualitative non-functional properties such as *customer satisfaction* or *user friendliness* can be described using an ordinal scale consisting of a set of predefined qualitative values, which we are referred to as ***qualifier tags***. For example, *High negative*, *Low negative, Low positive,* and *High positive* form the qualifier tags defined for the *customer satisfaction*. A qualifier tag represents a possible impact of functionality on a qualitative non-functional property. For example, the Credit card feature (i.e., functionality) has *high positive* impact on international sale; hence it can be annotated with the *High-positive* qualifier tag for *international sale*. On the other hand, metric based values are defined for the quantitative non-functional properties and can be measured for a product. For example, *performance* can be measured for and assigned to the Credit card feature. After measuring a non-functional value for features, the non-functional property of a product is computed by aggregating the non-functional values of features involved in the product. Based on the nature of NFPs, different aggregation functions can be plied [10][11].



(b)

Features \ NFP	Security	International Sale	Customer Satisfaction	Response Time	Cost	Availability	Reliability
Credit Card	LowN	HigP	MedP	50ms	$600	90%	95%
Debit Card	LowP	MedP	MedP	60ms	$450	90%	95%
Fraud Detection	HighP	LowP	HighP	40ms	$600	80%	98%

Figure 1: A subset of the on-line shopping systems feature model.

To compute the non-functional values of a product, for some NFPs such as cost and response time, the values are summed; while for others like availability and reliability values are multiplied. When optimizing NFPs for a product, we cannot use the same optimization technique for both qualitative and quantitative NFPs [18]. For example, because we cannot define a metric for customer satisfaction, it is hard to compute which feature selection leads to a product with the best customer satisfaction. On the other hand, we can find a selection of features, which results in a product with better performance.

Figure 1b shows non-functional properties employed in the on-line shopping product line. *Response time, cost, availability,* and *reliability* are quantitative non-functional properties and *customer satisfaction, international sale*, and *security* are qualitative non-functional properties.

2.3 Stakeholders' Preferences and Constraints

Non-functional properties do not have the same priority for the all stakeholders. For some stakeholders, a subset of non-functional properties may be more important and relevant than other non-functional properties. Moreover, in some situations, a conflict may arise between requirements defined over non-functional properties that have an opposite behavior, in case of which the stakeholder needs to choose between the competing options. One approach for specifying the priority between non-functional properties is through formalizing their *relative importance* relation. Relative importance is defined as follow [19].

Definition 2 (Relative Importance). Relative importance between non-functional properties a and b is: $a \succ^{\alpha} b$ iff non-functional property a is more important than non-functional property b with coefficient α.

Usually, the degree of importance of options (non-functional properties) is specified using values 1, 3, 5, 7, and 9 corresponding to equality, slight value, strong value, very strong and extreme value, respectively [22]. For example, relation $Security \succ^{3} Performance$ represents that *security* is slightly more important than *performance*. ***We refer to relative importance between non-functional properties as stakeholders' preferences.*** Prioritizing the stakeholders' preferences, formalized in terms of relative importance of non-functional properties, can have a dramatic impact on the design of the system.

In addition to preferences, stakeholders may define constraints over non-functional properties of a system. For example, a stakeholder may define a constraint that an on-line shopping system has to be at least *medium secure* and *cost* less than $1000. Thus, the final system should not have any functionality (i.e., feature) that provides positive impact on security less than the medium level. We assume that a product has some level of qualitative non-functional property (e.g., medium security), if all of its features have at least that level of non-functionality (i.e., all the features must have at least medium security).

Formally, we define stakeholders' preferences and constraints as:

Definition 3 (Stakeholders' Preference and Constraint Model). A stakeholder preference and constraint model is a triple $SPCM = (NFP, RI, CO)$ where 1) NFP is a set of non-functional properties; 2) RI is a set of relative importance relations between non-functional properties (Definition 2); and 3) $CO \subseteq NFP \times V$ is a set of constraints over the values of non-functional properties (the values in V can be either numeric values or qualifier tags based on the type of property).

2.4 Hierarchy Task Network (HTN) Planning

HTN planning fits well with domains consisting of low level actions and high level tasks. High level tasks are hierarchically refined into lower level tasks and finally into actions. HTN planning consists of a *planning domain*, *planning problem*, and an *output plan* [4]. Definition 4 formalizes an HTN domain [4].

Definition 4 (HTN Planning Domain). An HTN planning domain is a quadruple D = $(\mathcal{O}, \mathcal{T}, \mathcal{M}, \mathcal{V})$ where 1) $\mathcal{O}$ is a set of operators; 2) $\mathcal{T}$ is a set of tasks; 3) $\mathcal{M}$ is a set of methods; and 4) $\mathcal{V}$ is a set of domain predicates.

An *operator* (denoted as *o*) represents a low level action, which can be executed in the domain and is formally defined as a quintuple *o* = (*name(o), pre(o), eff(o), del(o), value(o)*). *pre(o)* defines a pre-condition for every operator, which represents required conditions for performing the operator. The effect of performing the operator can also be represented by using a post condition *eff(o). del(o)* or operator's delete list shows what becomes false after performing the operator. For every operator, an optional value *value(o)* can be defined, which shows a required cost for the execution of that operator. The total value of an output plan is the sum of the values of the operators in the plan.

The *task* construct (denoted as *t*) represents higher level activities in HTN and can recursively be decomposed into lower level tasks, and finally operators. In HTN, only operators can be executed and tasks can only be reduced into sub-tasks and operators [15]. Refinement of a task into sub-tasks is done using one or more *methods* (denoted as m_t) corresponding to the task. So, every *method* defines how a task is decomposed into lower level tasks or operators. A method is a quadruple *M* = (*name(m), task(m), pre(m), dec(m)*) where *task(m)* is a parent task, *pre(m)* is a pre-condition, and *dec(m)* is a list of subtasks into which the parent is decomposed. A precondition *pre(m)* defines a required condition for decomposing the parent task. A method is applied only when its precondition is satisfied [4].

The planning problem describes characteristics of a required plan – the objective, initial state, and constraints. The HTN planning problem is formally defined as follows [4]:

Definition5 (HTN planning problem). An HTN planning problem is a triple PP = $(\mathcal{S}, \mathcal{T}, \mathcal{D})$ where 1) $\mathcal{S}$ is a set of logical atoms (initial state); 2) $\mathcal{T}$ is a set of initial tasks; and 3) $\mathcal{D}$ is a planning domain description defined in Definition 4.

As a result of applying a planning technique, a plan containing a sequence of actions that satisfies the objective and the constraints defined in the planning problem is produced. HTN planning formulates the plan by recursively decomposing the tasks into subtasks until it reaches the primitive tasks, which can be performed [15]. Similar to [4], we define an HTN plan.

Definition 6 (HTN Plan). Let PP = $(\mathcal{S}, \mathcal{T}, \mathcal{D})$ be a planning problem defined according to Definition 5. A plan for planning problem PP is a double $\pi = (\mathcal{O}', c)$ where 1) $\mathcal{O}' \subset \mathcal{O}$ is a set of operators that will achieve tasks $\mathcal{T}$ from initial state $\mathcal{S}$ in domain $\mathcal{D}$; and 2) c is the total value of the plan.

3. Problem Statement and Infrastructure

In this section, we highlight the challenges of modeling non-functional properties in product lines and optimizing them for every product derived based on stakeholders' preferences.

3.1 Modeling Non-functional Properties

In the standard feature modeling notation [1], features mainly represent the functional aspects of a product line and non-functional aspects are often neglected. For example, in the online shopping, the *Credit card* feature refers to the functionality provided by the feature and no information regarding its quality such as performance is provided. Some researchers have extended the feature modeling notation with NFPs [20][18][38]. Similarly, we extended feature models with the notion of NFPs, which can be either qualitative or quantitative. In our approach, we assume that *atomic features* (i.e., leave features) in a feature model have concrete implementations. Non-atomic (i.e., non-leaf) features are used for variability and composition relationships of the atomic features. Hence, NFPs are defined for leaf features. If an intermediate feature contains implementations and non-functional properties, we create a mandatory child feature for the intermediate feature and assign the non-functional properties to the child feature. After identifying domain features, developing a feature model and implementing its atomic features, we can then analyze impact of features on NFPs. For qualitative NFPs, based on existing domain knowledge, the impact of each feature on non-functional properties can be identified and proper qualifier tags can be assigned to each feature's non-functional properties. On the other hand, quantitative NFPs for the features can be measured using a suitable metric and assigned to the features. We assume that some techniques, like those proposed in [21], can be employed to measure NFPs for each feature. Extended feature models are formally defined as follows:

Definition 7 (Extended Feature Model). An extended feature model is a nonuple EFM= $(\mathcal{F}, \mathcal{F}_{\mathcal{O}}, \mathcal{F}_{\mathcal{M}}, \mathcal{F}_{\mathcal{IOR}}, \mathcal{F}_{\mathcal{XOR}}, \mathcal{F}_{ic}, \mathcal{F}_{\mathcal{A}}, NFP, \mathcal{AQ})$ where 1) $\mathcal{F}, \mathcal{F}_{\mathcal{O}}, \mathcal{F}_{\mathcal{M}}, \mathcal{F}_{\mathcal{IOR}}, \mathcal{F}_{\mathcal{XOR}}, \mathcal{F}_{ic}$ stand for a feature model (FM) according to Definition 1; 2) $\mathcal{F}_{\mathcal{A}} \subseteq \mathcal{F}$ is a set of atomic features; 3) $\mathcal{AQ} \subseteq \mathcal{F}_{\mathcal{A}} \times (NFP \times V)$ is a set of pairs of atomic features and their annotation pairs of non-functional properties and their value.

3.2 Optimizing Stakeholders' Preferences

In the application engineering process, a concrete product is generated by configuring a feature model based on the target application requirements and by instantiating the reference architecture based on the configured feature model. Stakeholders of each application may have different preferences over NFPs that must be considered in the configuration process. Configuring a feature model based on the stakeholders' requirements and preferences usually means selecting features such that a feature model configuration satisfies the stakeholders' functional requirements and constraints and optimizes their preferences. To optimize the configuration with respect to preferences, feature ranks must be computed based on their impact on the NFPs which may be of different importance for the target stakeholders. Additionally, both qualitative and quantitative NFPs must be considered in the computation of feature ranks.

As mentioned in Sec. 2, the stakeholders' preferences are in the form of relative importance over non-functional properties. To calculate the absolute ranks of non-functional properties based on the preferences, we applied the *Stratified Analytical Hierarchy Process* (S-AHP) algorithm proposed in our previous work [14]. S-AHP is based on the Analytic Hierarchy Process (AHP) [22], which is a well-known pair-wise comparison method used to calculate the relative ranking of different options based on stakeholders' judgments. We used S-AHP because it enables ranking non-functional properties based on the defined relative importance between them; according to the study in [14], S-AHP is easy to use and does not need too much effort from stakeholders; and finally, it significantly reduces the number of needed pairwise comparisons. A complete description of S-AHP is outside of the scope of this paper and is available in [14].

To consider qualitative non-functional properties in feature ranks, the stakeholders or application engineers should provide a mapping function from qualifier tags onto real values. For example, for customer satisfaction, one can define the following mapping function.

$$\mathrm{M}_{customer\ Sat.}(QT) = \begin{Bmatrix} -1 & High\ negative \\ -0.5 & Medium\ negative \\ -0.25 & Low\ negative \\ 0.25 & Low\ positive \\ 0.50 & Medium\ positive \\ 1 & High\ positive \end{Bmatrix}$$

The other way for calculating the corresponding real-numbers for the qualifier tags of a qualitative non-functional property is to use S-AHP. In this way, stakeholders specify the relative importance between the qualifier tags of each non-functional property and S-AHP calculates the rank of each qualifier tag. For example, the stakeholder specifies that for the *international sale* property $High\ positive \succ^3 Medium\ positive$, which means a feature with high positive impact on *international sale* is slightly more important than the feature with medium positive on *international sale*. In both the methods (i.e., both the mapping function and S-AHP), we assume the values are normalized into the [-1, +1] range.

After defining the ranks of non-functional properties and the mapping function for the qualitative non-functional properties, we describe the following utility function to calculate the ranks of each feature based on an extension to [23]. The rank of features is calculated based on their impact on non-functional properties by considering preferences of the stakeholders formulated in terms of the weight of non-functional properties.

Definition 8 (Utility function). Let us assume there are α quantitative NFPs to be maximized, β quantitative non-functional properties to be minimized, and θ qualitative non-functional properties whose impact needs to be maximized. The utility function for feature *f* is defined as:

$$\mathcal{R}(f) = \sum_{i=1}^{\alpha} w_i \times \frac{q_i(f) - \mu_i}{\sigma_i} + \sum_{j=1}^{\beta} w_j \times \left(1 - \frac{q_j(f) - \mu_j}{\sigma_j}\right) + \sum_{k=1}^{\theta} w_k \times M_k(QT(f))$$

where *w* is the weight of each non-functional property calculated by S-AHP such that $0 \leq w_i, w_j, w_k \leq 1$ and $\sum_{i=1}^{\alpha} w_i + \sum_{j=1}^{\beta} w_j + \sum_{i=1}^{\theta} w_k = 1$ and $M_k(QT(f))$ returns the real number corresponding to quality tags of *k*-th non-functional property. μ and σ are the

average values and the standard deviation of the quantitative non-functional properties for all atomic features in the feature model.

The overall rank of a product is calculated by aggregating the ranks of features selected for the product. The aggregation function used for calculating the product rank depends on the aggregation functions, which exist over non-functional properties of a feature. As discussed in Sec. 2, some quantitative non-functional properties such as response-time are additive and the quality of a composition of features is computed by adding up the quality of features [10][11]. The second type of aggregation functions defined on quantitative non-functional properties is multiplication when the quality of composition is calculated by multiplying the quality of features involved in the composition. The multiplication type can be converted into an additive type by computing the logarithm values of non-functional values. For qualitative non-functional properties, a qualifier tag assigned to a feature represents a qualitative impact of the feature on the non-functional property. Considering the mapping function that maps the qualifier tags into real numbers, we can calculate the overall impact of a composition of features by adding the impacts of the features involved in the composition. Hence, the aggregation function over the utility functions of features is an additive function and the overall rank of a product is computed as $\mathbb{R}(P) = \sum_{f_i \in P} \mathcal{R}(f_i)$. In order to derive an optimal configuration (product) *P,* we need to select the features, which maximize $\mathbb{R}(P)$.

In addition to preferences, the stakeholders' functional requirements and constraints over non-functional properties must be considered. Hence, the configuration problem is concerned with selecting features that satisfy the functional requirements (i.e., the requested functionality) and constraints and optimize the preferences. Formally, the configuration problem and the configuration are defined as follows.

Definition 9 (Configuration Problem). Let $SPCM = (NFR, RI, CO)$ and EFM= $(\mathcal{F}, \mathcal{F}_O, \mathcal{F}_\mathcal{M}, \mathcal{F}_{\mathcal{IOR}}, \mathcal{F}_{\mathcal{XOR}}, \mathcal{F}_{ic}, \mathcal{F}_\mathcal{A}, NFP, \mathcal{AQ})$ be a: i) stakeholder's preference and constraint model; and ii) extended feature model as per Definitions 3 and 7. A configuration problem is a triple CP = $(EFM, SPCM, \mathcal{F}'_\mathcal{A})$, where EFM is an extended feature model, SPCM is the set of preferences and constraints over NFPs defined by the stakeholders, and $\mathcal{F}'_\mathcal{A} \subset \mathcal{F}_\mathcal{A}$ is a set of required atomic features.

Definition 10 (Configuration). Let CP =$(EFM, SPM, \mathcal{F}'_\mathcal{A})$ and EFM= $(\mathcal{F}, \mathcal{F}_O, \mathcal{F}_\mathcal{M}, \mathcal{F}_{\mathcal{IOR}}, \mathcal{F}_{\mathcal{XOR}}, \mathcal{F}_{ic}, \mathcal{F}_\mathcal{A}, NFP, \mathcal{AQ})$ be a configuration problem and extended feature model, respectively. A configuration is a double COF = $(\mathcal{F}^{"}, \mathbb{R}(\mathcal{F}^{"}))$ where 1) $\mathcal{F}' \subset \mathcal{F}^{"} \subset \mathcal{F}$ is a set of selected features; and 2) $\mathbb{R}(\mathcal{F}^{"})$ is the total rank of the configuration.

Therefore, in the configuration process, an application engineer deals with the selection of a set of features containing the stakeholders' required functionality. The total rank of the selected features is the maximum rank based on the stakeholders' preferences. To help application engineers in the configuration process, we propose applying an AI planning technique.

4. Automatic Feature Model Configuration

Having annotated a feature model with NFPs, the process for deriving a new product starts by selecting and deselecting features based on the stakeholders' requirements reflected through desired features and preferences expressed in terms of relative importance between NFPs. To automate the configuration process, we define transformation rules to convert a configuration problem to a planning problem. To do so, we develop transformation rules to represent extended feature models in the HTN formalism. The transformation is done in two steps: generating an HTN domain model from a feature model, and generating a planning problem from a configuration problem.

When transforming a feature model and the corresponding configuration problem into the HTN domain and HTN problem, we need to convert the maximization problem into a minimization problem, because the SHOP2 planner, used in our implementation, works on minimization only (Negating the ranks of features can do this).

4.1 Generating the HTN Domain

Considering the analogy between tasks in HTN and features in a feature model, there is a need to define task decompositions to reflect feature relations. The HTN method element is used to define decomposition of tasks into sub-tasks or operators. As mentioned in Definition 4, a method contains the parent task, a list of children, and a pre-condition. Here, we have two options: 1) we can define different methods with a common parent task; but, an HTN planner (i.e., SHOP2) for decomposing a task into sub-tasks selects just one method for each plan. Hence, this option is suitable for mapping the XOR relation to HTN; 2) we can also define one method for a decomposition in which all children can be considered a list of subtasks in the method. In this case, the HTN planner performs the method if and only if the preconditions of all subtasks or operators are satisfied. We can then use this option for defining AND-decomposition with mandatory child features. Also, before transforming an extended feature model into an HTN domain, a pre-processing step is done to replace optional and OR features. First, every OR group in the feature model is converted into a set of optional features with AND relations between them (Figure 2a). Next, similar to [29] for optional goals, every optional feature f^o is replaced with a new feature f^p which is decomposed into two alternative features f^o and f^d *where* f^d stands for a "dummy" feature (Figure 2b).

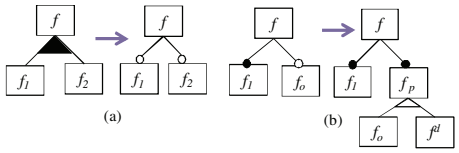


Figure 2: The preprocessing step for transforming feature models to HTN domains: (a) OR feature groups (b) optional features

After performing the above changes in the feature model, we transform the feature model into an HTN domain using the following three types of transformation rules: domain predicate transformation; operator transformation; method and task transformation.

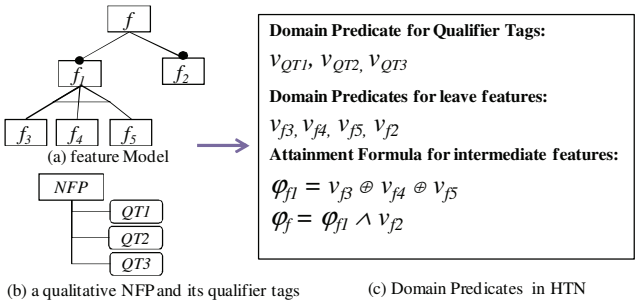
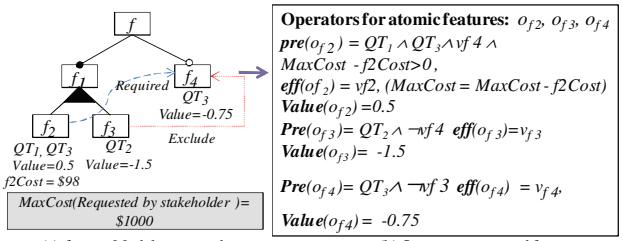


Figure 3: Generating Domain Predicates

Generating Domain Predicates. We generate domain predicates for each qualifier tag of the qualitative NFPs and atomic features in the feature model. For example, the v_{secnh} and v_{secph} predicates are created for *high negative* and *high positive* qualifier tags of the *security* non-functional property, respectively. Moreover, for features Credit Card and Debit Card, we generate domain predicates v_{cc} and v_{dc}, respectively. For each non-atomic feature, a propositional formula (called *attainment* formula [29]) is created according to the features that exist in its sub-tree (Figure 3). For instance, the attainment formula for feature Payment Gateway from Fig-

ure 1 is $\varphi_{PG} = v_{AN} \oplus v_{CS} \oplus v_{LP} \oplus v_P$. These formulae are later used for pre-conditions of the other features in the feature model.

Generating Operators. HTN operators are generated from atomic features in the feature model. Each atomic feature f is translated into an operator o_f and the rank of the feature calculated by the utility function is translated into $value(o_f)$. A precondition is defined for each operator based on the non-functional properties and integrity constraints defined over its corresponding feature. The preconditions are defined as logical AND expressions of: 1) domain predicates corresponding to qualifier tags of qualitative non-functional properties with which the feature is annotated; 2) an evaluation expression to check whether the feature is allowable to be selected or not based on quantitative non-functional properties constraints; and 3) attainment formula of features having *requires* and *excludes* relations with the feature (see Figure 4b). Next, the domain predicate, which corresponds to feature f (i.e., v_f) is added as an effect of the introduced operator (i.e., $eff(o_f) = v_f$). Whenever operator o_f is performed, its corresponding domain predicate becomes true (i.e., $v_f = true$). For handling quantitative NFP constraints, a logical atom is created showing the maximum available value of corresponding NFPs during the planning process. At the first, this value is set by the requested value of stakeholders and added to the initial state of the planning problem. Then, in the effect of each operator, this value is updated based on the assigned NFP value to the feature. For example, for the Fraud Detection feature in Figure 1, its corresponding operator has $value(o_{FD}) = 0.5$ (calculated by the utility function) and precondition $pre(o_{FD}) = v_{Sech} \wedge v_{ISI} \wedge v_{CSh}$, $(Maxcost\text{-}Cost_{Fraud\text{-}detection} > 0) \wedge (MaxResponsetime - Response\ time_{Fraud\text{-}detection} > 0)$. The operator corresponding to the Fraud Detection feature is performed only when its precondition is satisfied.

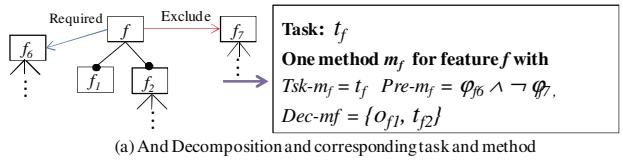


(a) feature Model, annotated with NFPs and feature ranks

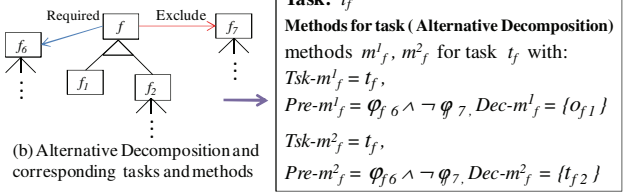
(b) Operators generated for atomic features

Figure 4: Translating Atomic features into Operators

Generating Tasks and Methods. For every non-atomic feature f, we define a task t_f and method(s) (m_{tf}). To create tasks corresponding to features, we use the pre-processed feature model from which OR feature groups and optional features have been removed (c.f. Figure 2). Based on the type of a feature group (i.e., XOR group or AND-decomposition), we may define one or more methods.



(a) And Decomposition and corresponding task and method



(b) Alternative Decomposition and corresponding tasks and methods

Figure 5: Generating tasks and methods from non-atomic features

If a feature f is AND-decomposed into features f_1 and f_2, we define one method which connects corresponding task t_f to tasks or operators corresponding to f_1 and f_2, (Figure 5a). For alternative feature groups with n sub-features (i.e., $f = XOR(f_1, f_2, .., f_n)$), n methods are defined with a common parent task t_f corresponding to feature f. Each method connects task t_f to one operator o_{fi} or task t_{fi} corresponding to the sub-feature f_i of the parent feature f (see Figure 5b). The precondition for every method is specified based on the attainment formula of features required by that feature and features excluded by that feature.

Table 1 gives the mapping rules between extended feature models (after eliminating OR and optional features) and the HTN domain.

Table 1: Mapping between constructs in extended feature models and HTN Domain models – OR and Optional feature Groups are replaced in the pre-procession step.

Extended Feature Model		*HTN Domain*	
Formal Rep	***Semantic***	***Formal Rep***	***Semantic***
$(NFP_i, qt_j) \in \text{NFP} \times \mathcal{QT}$	*Qualitative NFP and Qualifier tags*	$v_{NFP_i qt_j} \in \mathcal{V}$	*Domain predicates*
$f_i \in \mathcal{F}_{\mathcal{A}}$	*Atomic feature*	$o_{fi} \in \mathcal{O}$	*Operator*
$R(f_i)$	*Rank of atomic feature*	$value(o_{fi})$	*Property value of operator*
$(f_i, (NFP_j, qt_k)) \in AQ$	*Annotated feature with qualitative NFP and qualifier tag*	$pre(o_{fi}) \leftarrow v_{NFP_j qt_k}$	*Domain predicate as precondition of operator*
$(f_i, (NFP_j, v)) \in AQ$	*Annotated feature with quantitative NFP and its value*	$pre(o_{fi}) \leftarrow Maxv - v > 0$ $eff(o_{fi}) \leftarrow (Maxv = Maxv - v)$	*Evaluation as precondition and effect of operator*
$(f_i excludes f_j) \in \mathcal{F}_{ic}$	*Integrity constraints**	$pre(o_{fj}) \leftarrow \neg v_{ofi}$ $pre(o_{fi}) \leftarrow \neg v_{ofj}$	*Pre-condition for operator*
$(f_i requiers\ f_j) \in \mathcal{F}_{ic}$	*Integrity constraints**	$pre(o_{fi}) \leftarrow v_{ofj}$	*Pre-condition for operator*
$f = Xor_n^{i=1} f_i$	*Alternative feature group f*	$t_f, \cup_n^{i=1} m_f^i$	*One task and n method one for each alternative child*
$f = AND_n^{i=1} f_i$	*A feature f with set of mandatory child*	$t_f, m_f,$ $Dec\text{-}m_f = \cup_n^{i=1}$ t_{fi}	*One task, and one method with a set of sub-tasks*

**For simplicity in the representation, we considered the includes and excludes relations with atomic features, but features can also be non-atomic*

4.2 Generating the HTN Planning Problem

After defining the planning domain, the feature model configuration problem is transformed into the HTN planning problem (Table 2 summarizes the mappings). The transformation is done by considering the constraints over the NFPs (CO) and setting their corresponding domain predicates as true to form initial state ($\mathcal{S}$). For example, if a stakeholder asks for at least *medium security*, and a specific *cost* (e.g., $1000), the domain predicates $v_{secph} = true$ and $v_{secpm} = true$ and the rest of qualifier tags are set to *false;* the logical atom "*(cost 1000)*" is also added as an initial state. Next, the set of required atomic features ($\mathcal{F}'_{\mathcal{A}}$) and the root of the feature model are translated into initial tasks of the planning problem ($\mathcal{T}$).

5. Tooling and Methodology Support

As already indicated, SPLE methodologies include two processes [1][3][8], namely, domain engineering and application engineering. Assuming that a feature model has been annotated with non-functional properties, a target application can be developed by configuring the feature model reflecting the stakeholders' requirements and preferences.

In the configuration process, the application engineer captures the stakeholders' functional requirements including the required feature set ($\mathcal{F}'_{\mathcal{A}}$), the preferences (i.e., the relative importance of non-functional properties – RI), and the constraints over NFPs (CO).

By applying S-AHP and the utility function (Definition 8), which are implemented in our developed tool *Visual feature model plug-in* (called *Vis-fmp*) [1] – an extension of *feature model plug-in (fmp)* [16] – the ranks of NFPs (w_i) and features $\mathcal{R}(f_j)$ are computed, respectively. We employ an efficient planner (i.e. SHOP2), which uses a search-control strategy called *ordered task decomposition* to perform reasoning on the HTN planning domain [15].

Table 2: Mappings between the configuration problem and the HTN planning problem

Configuration Problem		*HTN Planning problem*	
Formal Rep.	***Semantic***	***Formal Rep.***	***Semantic***
EFM	*Extended feature model*	$\mathcal{D}$	*Domain description*
$(NFP_i, qt_j) \in CO'$	*Selected NFPs and qualifier tag*	$(v_{NFP_i qt_j} = \text{true}) \in \mathcal{S}$	*Initial state*
$(NFP_i, v) \in CO'$	*Constraint over quantitative NFPs*	$(NFP_i = v) \in \mathcal{S}$	*Initial state*
$f_i \in \mathcal{F}'_{\mathcal{A}}$	*Requested Feature*	$t_{fi} \in \mathcal{T}$	*Intial tasks*
f_{root}	*Root of extended feature model*	$t_{root} \in \mathcal{T}$	*Initial tasks*

The SHOP2 planner—a domain independent HTN planner—is automatically executed with its required inputs (i.e., HTN planning domain and HTN planning problem). The output of the planner is a set of planes (i.e., sequences of operators for the given tasks), which satisfy the initial conditions and have optimal value. The optimal configuration is achieved by selecting the features corresponding to the operators in the optimal plan. The result is shown to the stakeholders in a visual view that highlights the selected features and shows the corresponding NFPs along with features. Using the visual view, the stakeholders can navigate the configuration and perform changes in the configuration. Figure 6 shows a snapshot of a configuration in the visual view.

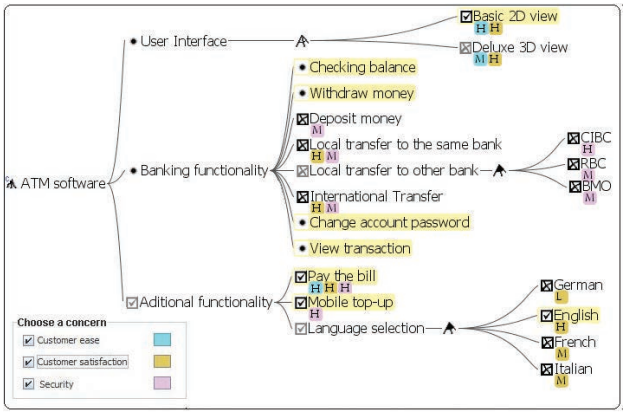


Figure 6: The result of planner in the visual view

6. Evaluation

To assess our technique and the corresponding tool *Vis-fmp,* we formulated the following research questions:

- **RQ1 (Scalability):** Can the approach configure feature models, in a reasonable time, based on functional and non-functional requirements and preferences?
- **RQ2 (Effectiveness):** How effective is the approach in producing a feature model configuration? **RQ2-1**: Does the approach generate reliable results for application engineers? **RQ2-2:** What is the automation level of the approach?

6.1 RQ1 (Scalability)

The purpose of this research question is to evaluate whether a feature model configuration can be performed in a reasonable amount of time. Hence, we conducted several experiments to investigate the research question.

6.1.1 Objects of Study

To evaluate the configuration approach, we adapt Betty FM Generator [34], which enables the random generation of highly-customized feature models, to generate feature models with different characteristics (e.g., number of features, probability of mandatory and optional features, probability of OR and XOR groups, and percentage of integrity constraints). We set the characteristics of generated feature models as: 50%, 25%, and 25% for probability of being features in AND, OR, and XOR groups, respectively. Moreover, 50% of features in AND groups are optional features. The branching factor is also set to 10. These characteristics are backed up by most of surveyed feature models [32] [33] to reflect the characteristics of real feature models.

Generating optimal configurations based on the stakeholders' preferences and constraints is NP-hard. Hence, HTN planners similar to CSP solvers have problems in finding optimal solution for large-scale problems. Although the SHOP2 planner applies some heuristics for improving search time for finding an optimal plan (See ref. [5]), due to explicit representations of states in the memory, SHOP2 runs into memory problems for large domains. However, our experiments showed for feature models with size of 200, SHOP2 returns an optimal plan in feasible time.

According to the results of investigation on non-functional properties done by [12], the number of relevant non-functional properties for different application domains is at most 11. Moreover, Sommerville and Sawyer [13] highlighted that the effective number of non-functional properties is around six. Considering these two studies, we defined 10 non-functional properties; six quantitative; and four qualitative non-functional properties. Five qualifier tags were defined for each non-functional property.

6.1.2 Experimental Setup

For each feature model, we applied our tool to configure the feature model based on preferences and constraints. The evaluation was performed on a computer with an Intel Core DUO 2.2 GHZ CPU, 4GB of RAM, Windows Vista, Java Runtime Environment v5.0, SHOP2 v2.8, and SBCL (Steel Bank Common Lisp) v1.0.55.

To configure the feature models, we considered three independent variables including *number of features*, *number of constraints*, and *integrity constraints*; and *time* as a dependent variable. For each feature model in the study, features were annotated with quantitative non-functional properties and their values were produced by a random function with normal distribution. From a practical point of view, only some of features (not all) may have impact on a qualitative NFP like security. Hence, to reflect this point, features were randomly annotated with 0 to 4 qualitative non-functional properties with normal distribution, that is, most of the features had one or two non-functional properties. Based on our analysis on SPLOT repository [7], which shows average of 18% of integrity constraints for the real feature models [31], we considered two distributions of integrity constraints: 10% and 20%. Finally, for the constraints over NFPs, four cases were considered: no constraint and constraints over 2,4, and 6 NFPs to reflect the effect of various constraints over NFPs at run time.

6.1.3 Experimental Results

Figure 7 illustrates the average time for configuring features models with different number of features and percentage of integrity

[1] https://files.semtech.athabascau.ca/public/projects/VIS-FMP/

constraints. Our experiments revealed that, for feature models with less than 200 features, the planner returns results in a feasible time (around 16 second). We also investigated the effect of constraints over NFPs on the running time of configuration technique proposed in the paper. To this end, we run the tool with feature models containing 100 features and 20% integrity constraints. The results are shown in Figure 8. In all of these situations, the process of generating optimal configurations was successful.

According to the experiment results, all three independent variables (i.e., *number of features*, *number of constraints*, and *integrity constraints*) have an impact on running time. As shown in Figure 7, for the fixed size of integrity constraints, increasing the number of features raises the time for finding optimal configuration, as increasing the number of features expands the search space for finding optimal plan. Also, within the same number of features, the increase of integrity constraints from 10% to 20% causes increase the time for finding a plan, as the planner needs to check more pair combinations of tasks and operators for optimizing a final plan.

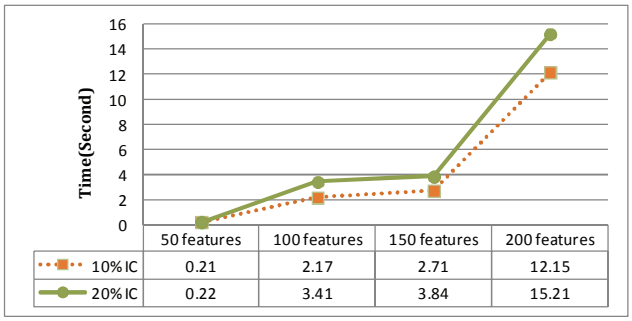


Figure 7: Running time of the configuration technique for feature models with different numbers of features and integrity constraints.

Finally, as illustrated in Figure 8, constraints over NFPs have a significant impact on increasing the time for configuration, even if the number of features and integrity constraints are fixed. According to the results of the experiment, the impact of constraints over NFPs is higher than the impact of integrity constraints.

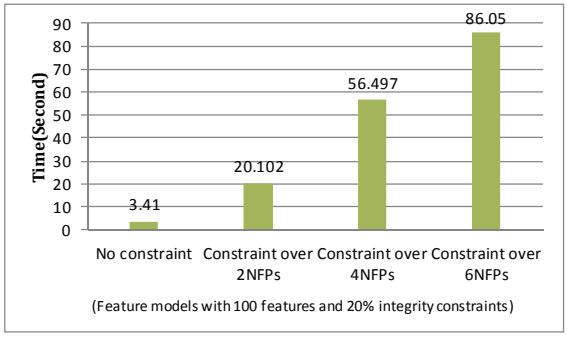


Figure 8: Running time of configuration technique based on different number of constraints over NFPs

6.2 RQ 2(Effectiveness)

This research question aims to investigate if application engineers can trust the results returned by the planner and if the approach is beneficial for stakeholders to facilitate their tasks.

Regarding the reliability of the results, our approach is based on transforming feature models into the HTN formalisms and applying SHOP2 to find an optimal configuration. According to the framework proposed in [27], we can investigate if these representations are surrogate for representing feature models and preferences. As shown, we can represent feature model relations and constraints using existing constructs in HTN such as method, tasks, and operator. Additionally, operators provide properties to define a feature rank. The constraints over non-functional properties and integrity constraints can be defined as precondition of operators and method. Hence, we can consider HTN to be a surrogate for feature models. With respect to the ontological commitment, HTN views the world as a set of actions, tasks, constraints between them; this makes it suitable for representing both feature model and constraints. With respect to the planner, SHOP2 have been extensively applied in many projects [30] in government laboratories (e.g., evacuation planning), industry (e.g., evaluating of enemy threats), and academia (e.g., automated composition of Web services), which shows the usefulness of the returned plans and their corresponding configurations.

One way to facilitate the application engineers' tasks during the configuration process is through automating their task. With respect to the automation level, our approach requires only very few manual interventions. The main tasks of the application engineers are: 1) specifying the relative importance of non-functional properties; 2) creating the mapping function for qualitative non-functional properties; and (3) specifying the atomic features that must be included based on the functional requirements. Computing ranks of non-functional properties based on preferences and finding optimal solution are fully automated in our approach.

7. Related work

To systematically compare the approach, we devise a number of criteria that need to be supported by configuration techniques in order to be effective for application engineering. To define the criteria for systematic comparisons, similar to [37], we applied bottom-up and top-down approaches. Following the bottom-up approach, we identified various important aspects of feature model configuration in description of existing related works and added them to the criteria set. Following the top-down approach, we used an existing survey on configuration of software product lines. We do not claim that this criteria set is complete, but it provides appropriate aspects to compare our work with related works. These criteria include: 1) Managing functional and non-functional requirements; 2) Modeling stakeholders' preferences; 3) Optimization; 4) Considering stakeholder constraints; 5) Providing tooling support; 6) Automating configuration process; 7) Ensuring the feature model constraints; 8) Effective representation of results to stakeholders; 9) Time efficiency.

In the following subsections, we review existing configuration techniques and compare them w.r.t. the above criteria.

7.1 Feature Model Configuration Approaches

The first attempt, important for our research, is by Czarnecki et al. [17] who introduced a stage configuration process. In that work, a number of configuration steps are introduced to remove variability from feature models. A final product is developed by a consecutive specialization of the feature model through different specialization steps. In each specialization step, some part of the feature model variability is resolved.

Benavides et al. [20] developed an automated reasoning technique over extended feature models (i.e., feature models with extra-functional features). Using their extension, they were able to assign extra-functionality such as price range or time range to features. The purpose of their technique is to find a product of a model based on given constraints. Their technique is based on mapping feature models to CSPs and use of CSP solvers [20][35]. Siegmund et al. [18] have developed a technique called *SPL conqueror* which extends feature models with non-functional properties and applies CSP to find optimal configuration based on user defined objective functions. In their technique, a number of preprocessing steps are taken to reduce the search space for optimal configuration.

White et al. [25] used a *Filtered Cartesian Flattening* (FCF) method to select optimal feature sets according to resource constraints.

In their method, they map the feature selection problem to a *multi-dimensional multi-choice knapsack problem* (MMKP) [25]. By applying existing MMKP approximation algorithms, they provide partially optimal feature configurations in polynomial time. White et al. [26] also formalize stage configuration and introduced a *Multi-step Software Configuration probLEm solver* (MUSCLE) in which they provide a formal model for multi-step configuration and map it to CSPs. Hence, CSP solvers were used to determine the path from the start of the configuration to the desired final configuration. They consider non-functional properties such as cost constraints between two configurations and formalize them as CSP constraints. Their approach is only applicable for multi-stage configuration and focuses on creating new configurations from an already derived product configuration.

Mendonca et al. [24] proposed a translation of basic feature models into propositional logics and used Binary Decision Diagrams (BDD) as the reasoning system. Their approach concentrates on validating feature models and does not offer a facility for automated configuration. It can be used in a multi-stage configuration process to validate the results of every specialization of a feature model (called interactive configuration). An interactive configuration only checks the structural constraints of feature models and does not consider preferences and non-functional requirements. A tool is implemented to support software developers in validation.

Guo et al. also addressed the challenge of optimizing feature model configuration in their work [36]. They proposed an approach in which Genetic Algorithms are employed to optimize Feature Selection (GAFES).

7.2 Comparing the approaches

Table 3 summarizes the results of the comparison of the approaches based on the criteria identified earlier.

Managing functional and non-functional properties. Stage configuration [17] and the work in [24] provide no guideline for configuration of non-functional properties. FCF [25], MUSCLE [26], and the technique from [20] support selection of features only based on quantitative non-functional requirements. Our approach and SPL conqueror [18] guarantee the selection of features based on functional and non-functional properties. Furthermore, only SPL conqueror [18] and our approach consider both qualitative and quantitative non-functional properties.

Modeling stakeholders' preferences. CSP based approaches [18][26], FCF [25], and GAFES [36] model stakeholders' preferences in terms of user defined objective functions. Considering the diversity of non-functional properties, it is not easy for stakeholders to define an objective function, which reflects their preference. However, our approach provides a systematic and easy technique to capture stakeholders' preference in terms of relative importance and defines the objective function using these inputs. Stage configuration does not provide any support for stakeholders' preferences.

Optimization and time efficiency. Generating optimal configurations based on the stakeholders' preferences and constraints is NP-hard. All CSP approaches [20][18][26] and our approach ensure optimality of the solution, but they require high computation time. To compare the running time of our approach with CSP approaches, we had limitations. The tool developed by Benavides et al [20], called FAMA, does not support optimization which makes it hard to compare with. The SPL conqueror tool is not publicly available and MUSCLE does not have tool support. FCF [25] and GAFES [36] provides partially optimal solutions in a polynomial time. Stage configuration and the work in [24] do not support optimization of the stakeholders' requirements.

Considering stakeholders' constraints. Stakeholders may define constraints based on the resources that are available to them and level of non-functionality. These constraints need to be considered and only a configuration which satisfies the stakeholders' constraints and optimizes the preferences must be produced. FCF [25], GAFES [36], and CSP based approaches [20][18] [26] support constraints on the stakeholders' resources. On the other hand, our approach handles constraints over both qualitative and quantitative non-functional properties.

Tooling support and automation. All the approaches, except FCF, provide tooling support. Stage configuration provides tooling support, but little automation for feature model configuration is provided. With respect to the usability, our approach and SPL conqueror [18] apply visualization techniques to present the configuration results to the stakeholders. Our tool shows the quality level of selected features along with them in the same view (Figure 6). Other tools provide basics views for representing configurations to the stakeholders.

Feature model integrity constraints. All approaches, except [20] ensure the satisfaction of integrity constraints (i.e., requires and excludes relations) during configuration. .

Table 3: Comparative analysis of related works ((+) criterion met, (–) criterion not met, (+/-) criterion partially met)

Criteria / *Approach*	FR/NFR	Preference	Optimization	Constraints	Automation	Integrity constraints	Tooling support	Time efficiency
Stage Configuration Czarnecki et al. [17]	+/-	–	–	–	–	+	+	–
CSP - Benavides et al. [20][35]	+/-	-	+	+	+	–	+	–
FCF White et al. [25]	+/-	+/-	+/-	+	+	+	–	+
SPL Conqueror Siegmund et al [18]	+	+/-	+	+	+	+	+	+/-
MUSCLE White et al. [26]	+/-	+/-	+	+	+	+	–	+/-
Mendonca et al. [24]	+/-	–	–	–	+	+	+	+
GAFES Guo et al. [36]	+/-	+/-	+/-	+	+	+	+	+
Our approach	+	+	+	+	+	+	+	+/-

8. Conclusion

In this paper, we targeted an open research question in software product lines: how to select a suitable set of features from a feature model based on both the stakeholders' functional and non-functional requirements and preferences. We formalized the configuration problem as an HTN planning process and employed an existing HTN planner to generate an optimal configuration based on the stakeholder preferences and constraints over non-functional properties. The experimental results revealed that our approach can be very useful as: 1) it provides an optimal configuration based on stakeholders preferences and constraints over non-functional properties; and 2) it has a good performance on feature models with sizes less than 200 features (Sec. 6). For larger feature models, the approach is computational demanding, similar to other related approaches in the literature (Sect. 7). Another HTN planner (called HTNPLAN-P [4]) applies new heuristics and can support larger planning space problems, so that the practical performance time can be much improved as shown in [4]. Since HTNPLAN-P is not yet publicly available, we could not test our work on larger feature models. In the future work, we will try to implement such a heuristics and perform additional experimentations.

9. REFERENCES

[1] K. Kang, S. Cohen, J. Hess, W. Nowak, and S. Peterson. Feature-Oriented Domain Analysis (FODA) Feasibility Study. Technical Report, CMU/SEI-90-TR-21, PA, November 1990

[2] J. Bosch, Design and Use of Software Architectures: Adopting and Evolving a Product-Line Approach. ACM Press, Add-Wesley, 2000.

[3] F. Linden, K. Schmid, E. Rommes, Software Product Lines in Action - The Best Industrial Practice in Product Line Engineering. Springer, Berlin, Heidelberg, Paris, 2007.

[4] S. Sohrabi, J. A. Baier, and S. A. McIlraith, "HTN planning with preferences," in Proc. 21st Int'l Jont Conf. Artifical intelligence, 2009, p. 1790–1797.

[5] D. Nau, Y. Cao, A. Lotem, and H. Munoz-Avila, "SHOP: simple hierarchical ordered planner," in Proc. 16th int'l joint conference on Artificial intelligence - 1999, p. 968–973.

[6] L. Olsina, G. Lafuente, and G. Rossi, "Specifying Quality Characteristics and Attributes for Websites," in Web Engineering, vol. 2016, S. Murugesan and Y. Deshpande, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 266-278.

[7] Software Product Line Online Tools (SPLOT), http://www.splot-research.org/, accessed April 2011.

[8] K. Czarnecki, and U. Eisenecker, Generative Programming: Methods, Tools, and Applications. Addison-Wesley, 2000.

[9] S., Robertson, J., Robertson, Mastering the requirements process. New York: ACM Press, (1999).

[10] F. Rosenberg, P. Celikovic, A. Michlmayr, P. Leitner, and S. Dustdar, "An End-to-End Approach for QoS-Aware Service Composition," Proc. IEEE EDOC Conf., 2009, pp. 151-160.

[11] T. Yu and K.-J. Lin, "Service selection algorithms for Web services with end-to-end QoS constraints," Information Sys. and e-Business Management, vol. 3, no. 2, pp. 103-126, 2005.

[12] D. Mairiza, D. Zowghi, and N. Nurmuliani, "An investigation into the notion of non-functional requirements," In Proc. 2010 ACM Symp. on Applied Computing 2010, pp. 311–317.

[13] I. Sommerville, P. Sawyer,, "Viewpoints: principles, problems and a practical approach to requirements engineering," Annals Soft. Eng., vol. 3, p. 101-130, 1997.

[14] E. Bagheri, M. Asadi, D. Gasevic, and S. S, "Stratified analytic hierarchy process: prioritization and selection of software features," in Proc. Software Product Lines Conf., 2010, p. 300–315.

[15] D. Nau et al., "Applications of SHOP and SHOP2," Intelligent Systems, IEEE, vol. 20, no. 2, pp. 34-41, 2005.

[16] K. Czarnecki and E. al., "Cardinality-Based Feature Modeling and Constraints: A Progress Report," OOPSLA'05, 2005.

[17] K. Czarnecki , S.Helsen, and U.Eisenecker, "Staged configuration using feature models,"in Proceeding of the Software Product Lines conference, (2004), 162–164.

[18] N. Siegmund, M. Rosenmüller, M. Kuhlemann, C. Kästner, S. Apel, and G. Saake, "SPL Conqueror: Toward optimization of non-functional properties in software product lines," *Software Quality Journal*, 2011.

[19] I. Ognjanovic, D. Gašević, E. Bagheri, and M. Asadi, "Conditional preferences in software stakeholders' judgments," ACM SAC 2011, p. 683.

[20] D. Benavides, P. Trinidad, and A. Ruiz-Cortés, "Automated Reasoning on Feature Models," *in Proc. 17th Int'l conf. Advanced Information Systems Engineering,* pp. 491–503., 2005.

[21] N. Siegmund, M. Rosenmüller, C. Kästner, P. Giarrusso, S. Apel, and S.Kolesnikov. Scalable Prediction of Non-functional Properties in Software Product Lines. In Proc. Software Product Line Conf., pp.160–169. 2011

[22] T.L., Saaty, The Analytic Hierarchy Process. McGraw-Hill, New York (1980).

[23] T. Yu and K.-jay Lin, "K.: Service selection algorithms for composing complex services with multiple qos constraints," In Proceedings of the 3rd Conference on Service-oriented Computing, p. 130--143, 2005.

[24] M. Mendonca, A. Wasowski, K. Czarnecki, and D. Cowan, "Efficient compilation techniques for large scale feature models," in *Proceedings of the 7th international conference on GPCE,* 2008, p. 13–22.

[25] J. White, B. Dougherty, and D. C. Schmidt, "Selecting highly optimal architectural feature sets with Filtered Cartesian Flattening," J. Systems & Software, vol. 82, p. 1268–1284, 2009.

[26] J. White, B. Dougherty, D. C. Schmidt, and D. Benavides, "Automated reasoning for multi-step feature model configuration problems," in *Proceedings of the 13th International Software Product Line Conference*, 2009, p. 11–20.

[27] R. Davis, H. Shrobe, and P. Szolovits, "What is a knowledge representation?" AI magazine 14, 1 (1993), 17.

[28] M. Bienvenu and S. McIlraith. Specifying and Generating Preferred Plans. *Working Notes of the Seventh International Symposium on Logical Formalizations of Commonsense Reasoning,* May 2005, Kerkyra, Greece.

[29] S.Liaskos, S.A.McIlraith, S.Sohrabi, and J. Mylopoulos. Integrating Preferences into Goal Models for Requirements Engineering. 18th IEEE Int'l RE Conf., (2010), 135–144.

[30] D. Nau et al., "Applications of SHOP and SHOP2," IEEE Intelligent Systems, vol. 20, pp. 34-41, Mar. 2005.

[31] E. Bagheri and D. Gasevic, "Assessing the maintainability of software product line feature models using structural metrics," Software Quality Journal, 2011.

[32] J. Guoa, J. Whiteb, G. Wanga, J. Lia, and Y. Wanga, "A Genetic Algorithm for Optimized Feature Selection with Resource Constraints in Software Product Lines."

[33] T. Thum, D. Batory, and C. Kastner, "Reasoning about edits to feature models," in *Proceedings of the 31st International Conference on Software Engineering*, 2009, pp. 254–264.

[34] Betty Feature Model Generator Version 1.1, http://www.isa.us.es/betty/.

[35] D. Benavides, S. Segura, P. Trinidad, and A. Ruiz-Cortés, "Using Java CSP solvers in the automated analyses of feature models," *Generative and Transformational Techniques in Software Engineering*, pp. 399–408, 2006.

[36] J. Guo, J. White, G. Wang, J. Li, and Y. Wang, "A genetic algorithm for optimized feature selection with resource constraints in software product lines," *Journal of Systems and Software*, vol. 84, no. 12, pp. 2208–2221, Dec. 2011.

[37] K. Schmid, R. Rabiser, and P. Grünbacher. 2011. A comparison of decision modeling approaches in product lines. In Proceedings of the 5th Workshop on Variability Modeling of Software-Intensive Systems, 119-126.

[38] E. Bagheri, T. D. Noia, D. Gasevic, and A. Ragone, "Formalizing interactive staged feature model configuration," *J Software Maintenance and Evolution: Research and Practice.*