Empirical Validation of Structural Metrics to Assess and Predict Usability of SPL Feature Model

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ABSTRACT

Early assessment of quality is a primary concern for all disciplines of software engineering. In case of Software Product Line (SPL) engineering also, it is acknowledged that quality assessment should be given special attention during its early phase (domain engineering). The reason being, that defects unobserved early in the domain artefacts will later affect other products of the product line and will lead to increased costs for correcting the defects in the later stages. During domain engineering phase, feature models play an important role in designing these domain artefacts. They diagrammatically represent the product line commonality and variability during the early stages of development. Therefore, their quality assessment too holds importance. While quality aspects of SPL architecture have being widely researched, the quality assessment of feature models has been neglected till now.

Unfortunately, the contemporary metrics applicable for quality assessment of object oriented, single system engineering don't suffice for assessing quality of SPL. Thus, evolution of novel approaches for quality assessment during domain engineering phase is much needed. In the previous research a set of structural metrics were designed to evaluate SPL feature model usability. In the previous work, they were validated theoretically against standard frameworks. In the current research, the theoretically validated structural metrics were validated empirically for assessing usability (from the designer's perspective) in reference to feature models. The results obtained from the controlled experiment show that the structural metrics are significantly correlated with usability of feature models. A formula on the basis of linear regression is also designed to estimate the level of usability. Based on the empirical results it is concluded that the designed structural metrics are a strong means of quality assessment for examining SPL feature model usability. Quality assessment of SPL feature models can be done using the structural metrics and eventually quality can be examined during the early stages of SPL development.

Keywords: Feature Models, Metrics, Quality assessment, Software product lines.

1- INTRODUCTION

Early quality assessment is a vital issue for all types of software development and especially for software product line engineering (SPL). SPL is a novice approach to develop set of software which belongs to the same product line [1][2]. Development process in SPL includes two phases: domain engineering and application engineering; and quality assessment should be conducted in both the phases [3]. Domain engineering is the initial stage of product line engineering, where all artefacts like requirements, design, or variations are defined keeping in mind reusability. These artefacts sum up into the software product line variability and commonality. Quality assessment has to be done ensuring quality of all the artefacts. During application engineering which is the later stage, as per customer requirement these variations are combined into specific products. In this phase also quality of individual products has to be ensured. Out of both the phases, quality assessment should be given more attention during domain engineering. The reason being, that if defects prevail in the domain artefacts their reuse during application engineering will lead to defective products in the product line and will also result in increased costs for correcting the defects in the later stages [4]. Also because variability of domain engineering increases overall complexity of the software product line, quality assessment in this phase becomes imperative at the same time challenging.

In order to characterize all achievable combinations of assets, feature models are often used [5]. They were first introduced by Kang [6]. A feature diagram is the graphical representation of the feature model. It consists of features in hierarchy. It has following types of features: Mandatory: the feature must be included with its parent feature, optional: the feature may or may not be included with its parent feature, or: one or more features can be included with its parent feature. One and only one feature can be included with its parent feature. Figure 1 consists of a sample feature of a sample feature diagram of E-shop SPL.



Figure 1. Sample feature mode of E-shop

To derive a final product from an SPL, a customer can use the feature model to select features needed in the final product. Specific combination of various features is called a configuration [7]. As quality assessment is preferable

during the initial stages of SPL development, quality assessment should begin while designing the feature models.

Metrics provide an important way towards assessing and improving the software quality. They can be used to understand, control, and improve product development phase [8]. Traditionally, metrics are categorized as code and structure based. Structural metrics assess the physical composition and configuration of the system. This makes these metrics early indicators of product quality [9]. Literature review reveals that several metrics are proposed and studied but all are limited to the domain of object oriented systems, UML diagrams, and program code [10] - [23]. These contemporary measures cannot be applied directly over feature models because feature models constitute of features rather than classes and objects. Thus a need of structural metrics for assessing the structural complexity of the feature models was realized.

But, there is little reference about structural metrics for feature models in the existing literature. Therefore, in the previous research work, few structural metrics were formally proposed and theoretically validated [24]. The next step to theoretical validation is empirical validation of the structural metrics in reference to SPL feature models. The objective of the current study is to study the correlation between the designed structural metrics and feature model usability in the first step. In the second step prediction models are developed and the prediction accuracy of the structural metrics will be analyzed in reference to SPL feature model usability.

The paper is structured as follows: section 2 contains a brief description about the structural metrics to be validated empirically. In section 3 the experimental design is discussed. Section 4 contains the result and analysis of the experiment and section 5 presents the conclusion of the research, followed by references.

2- STRUCTURAL METRICS FOR ASSESSING FEATURE MODEL USABILITY

The description of metrics proposed previously to assess the level of usability of feature models is shown in Table 1. These metrics aim to measure usability of SPL feature models. They were designed under three categories. The categories and their metrics are:

- 1) Metrics based on Formation of feature model CAltOpt, CStAltF, CStOptF, DtConf, RSWgAltMand, RSWgOptMand, SWgTHC.
- 2) Metrics based on Relationships that exists between various features CPf, DtNf,DtNfCC,RCPC,SWgC,SWgT,WdT

 Metrics based on Weight depending upon the type of feature: CFWg1, CFWg2, CFWg3, CPWg1, CPwg2, CPwg3 ,MSWgSt, WgDtConf, wgDtConfCC.

Metrics Name	Description
CAltOpt	Count of all features except mandatory
CFWg1	Count of total mandatory features
CFWg2	Count of total or features
CFWg3	Count of total optional and alternative features
CPf	Count of parent features
CPWg1	Count of "mandatory" parent features
CPWg2	Count of "or" parent features
CPWg3	Count of alternate and optional parent features
CStAltF	Count of subtrees having alternate feature
CStOptF	Count of subtrees having optional feature
DtConf	Depth of tree+(ratio of optional features over all features in the model), DT+FOC
DtNf	Depth of tree+number of features-1; DT-NF-1
DtNfCC	(depth of tree+number of features-1)+ number of constraints in the model; (DT+NF-1)+CC
MSWgSt	Maximum weight of all the subtrees
RCPC	Ratio of count of parent features over count of child features in the model
RSWgAltMand	Ratio of sum of weight of alternate features over sum of weight of mandatory features
RSWgOptMand	Ratio of sum of weight of optional features over sum of weight of mandatory features
SWgC	Sum of weight of all child features

Table 1. Description of the Designed Structural Metrics

SWgT	Sum of weight of the whole tree
SWgTHC	Sum of weight of tree with heaviest configuration
WdT	Total number of features/maximum depth
WgDtConf	Weight applied on metric number 11
WgDtConfCC	Weight applied on metric number 13

3- EXPERIMENTAL DESIGN

Following the GQM template the goal for the experiment was defined [25]. GQM is a standard benchmark for proposal of software metrics. Without including the proper context and goal of measurement, it remains unclear which metrics should be proposed and how to interpret the selected metrics. GQM helps in defining the metrics, and evaluating the practical usefulness of the proposed measure. It consists of three levels: Conceptual level, Operational level, and Quantitative level. Table 2 shows the goal of the experiment set with the help of GQM.

Analyze	Structural complexity metrics for SPL feature models			
For the purpose of	Evaluating			
From the point of view of	Researchers			
In the context of	MCA semester V students			

Table 2. GQM to Set the	Experimental Goal

3.1 HYPOTHESIS

The foundation of any empirical study is to define and validate the hypothesis. The objective of this experiment is to study the association of structural metrics with usability attributes. The experiment aims to analyze whether the structural measures proposed for SPL feature models are suitably serving as indicators for the evaluation of usability or not. The hypothesis is as follows:

Null hypothesis H₀: There is no significant correlation between the structural metrics and usability of SPL feature models.

Alternative hypothesis $H_{1:}$ There is a significant correlation between the structural metrics and usability of SPL feature models.

3.2 VARIABLES

In any experimental study variables play an important role. They help in accurately measuring the hypothesis. The two variables for the experiment are:

Independent Variables: The independent variables are the structural metrics. They are categorized as independent because within the cause-effect relationship which is of major concern, they represent the cause, i.e. whether these metrics are or not correlated with SPL feature model usability (and its sub characteristics).

Dependent Variables: According to ISO 9126 usability is a vital external quality attribute [26]. It can be easily explained in terms of its three sub characteristics viz. learnability, understandability, and communicativeness[27] - [29]. Because external quality attributes represent the effect in the cause-effect relationship, in this experiment the dependent variables are the three sub characteristics of usability.

3.3 CONTEXT SELECTION AND OBJECTS OF STUDY

The context of the experiment is group of MCA V Semester students from different colleges across Rajasthan. Total 142 responses were received.

The objects of the study are SPL feature models. The feature models included in the experiment are picked from Software Product Line Online Tools (SPLOT) [30]. All the feature models were properly validated and checked for possible dead features. Different domains were kept in mind while finalizing the models. Total 13 feature models in English language were selected keeping in mind their understandability by the subjects of the study.

3.4 DATA COLLECTION

The subjective perception of the participants was obtained through questionnaires. The process to gather the subjective perception was as follows: the participants had already taken a course in software engineering; prior to the experiment they were given a demo class regarding SPL feature models. The participants were kept unaware about the aspects and hypothesis of the study. They were given time to communicate their queries about the models and their semantics. After this they were given the questionnaires to assess their subjective perception. In the questionnaire, each question consist a set of 3 sub questions (one for each sub characteristic) for all 13 models. The questions inquired the level of usability of the models on the basis of 7 point Likert scale.

The subjects were provided the questionnaire post the demo class. They were counseled about carrying out the experiment. They were allowed a day's time to do the experiment, each subject carried out the test alone. The questionnaire data was collected in the form of subject's rating of the experiment. The metrics values were calculated manually.

4- **RESULTS AND ANALYSIS**

4.1 RELIABILITY ANALYSIS

Once the values for both the variables were obtained, the Chronbach's Alpha Reliability test was applied. The results of this test are significant as the subjects should reach a certain level of agreement else convincing conclusions cannot be drawn on the basis of the collected data. The Cronbach's Alpha test retrieves the level of similarity among the qualitative behavior of the participants. Results obtained from the test are shown in table 3.

Table 3. Reliability Analysis				
Cronbach's Alpha	Number of Items			
033	3			

As seen in the above table, the degree of reliability of all the participants is higher than 0.7. It indicates that there exists a reasonable agreement between the participants. In other words there is a fair resemblance or homogeneity between the opinions of all the participants. As a result of this reliability analysis, it was concluded that the opinion of the participants was reliable enough for further analysis.

4.2 METRICS INDICATIVENESS STUDY

The next step of the experiment was to ascertain if any correlation exists between the dependent and independent variables. Pearson's Correlation Test was applied to determine the correlation for metrics indicativeness. The results are contained in table 4.

	Learnab ility	Understa ndability	Communi cativenes s
TF	010	.127	.120
	.974	.679	.696
CPf	433	321	309

Table 4. Metrics Indicativeness

	.139	.285	.304
CAltOpt	326	228	276
САПОрі	.276	.454	.361
	186	256	296
CEWGI	.543	.399	.326
	510	310	301
CFWgz	.075	.302	.317
	580 [*]	566*	511
CEW95	.038	.044	.074
	.139	.184	.259
CEWGI	.360	.548	.394
	513	.265 .228 .454 256 .399 310 .302 .566* .044 .184 .548 291 .335 .595* .032 .032 .032 .032 .032 .000 1.000 434 .138 .121 .694 .697** .008 715** .006 .117 .702 .225 .460 .191 .531 .695** .008 191 .531 .695** .008 .117 .702 .225 .460 .191 .531 .695** .008 .687** .009 .141<	347
	.073	.335	.246
CBwa?	.139 326 - $.276$ $$	595*	571*
CF Wy3	.077	.032	.042
CStOptE	057	326 228 326 228 276 $.454$ 186 256 543 $.399$ 510 310 075 $.302$ 580° 566° 038 $.044$ 277 $.184$ 360 $.548$ 513 291 073 $.335$ $.507$ 595° 077 $.032$ 057 $.000$ 853 1.000 $.519$ 434 069 $.138$ 072 $.121$ 814 $.694$ $756^{\circ \circ}$ $697^{\circ \circ}$ 003 $.008$ $769^{\circ \circ}$ $715^{\circ \circ}$ 002 $.006$ 235 165 $.440$ $.590$ 075 $.117$ 807 $.702$ 062 $.225$ 840 $.460$ $.359$ $.191$ <td>011</td>	011
Союріг	.853	1.000	.972
	519	434	386
COLAILE	.069	39 .285 326 228 76 .454 186 256 43 .399 510 310 77 .302 80° 566^\circ 38 .044 777 .184 600 .548 513 291 77 .032 957 .000 53 1.000 519 434 69 .138 072 .121 14 .694 56^{**} 697^{**} 003 .008 69^{**} 165 40 .590 075 .117 002 .006 235 165 40 .590 075 .117 007 .702 062 .225 40 .460 359 191 229 .531 38^{**}	.193
DtConf	072	.121	.230
	326 22 $.276$ $.455$ 186 26 $.543$ $.39$ 510 31 $.075$ $.30$ 580° 56 $.038$ $.04$ $.277$ $.18$ $.360$ $.544$ 513 26 $.073$ $.33$ 507 59 $.073$ $.33$ 507 59 $.077$ $.03$ 519 43 $.069$ $.13$ 057 $.00$ $.853$ 1.00 519 43 $.069$ $.13$ 072 $.12$ $.814$ $.69$ $.075$ $.11$ $.002$ $.000$ 235 16 $.440$ $.59$ $.075$ $.11$ $.807$ $.700$ $.062$ $.222$ $.840$ $.46$ 359 16 $.229$ $.53$ 738^{**} 69 $.003$ $.000$ 749^{**} 68 $.003$ $.000$ 199 14 $.515$ $.64$.694	.450
DtNf	756**	697**	671*
	.003	.008	.012
	769**	715**	673*
	.002	.006	.012
MSWaSt	235	165	023
wowyou	.440	.590	.940
RCPC	.075	.117	.045
	.807	.702	.884
RSWgOptM	.062	.225	.219
and	.840	.460	.472
RSWgAltMa	359	191	181
nd	.229	.531	.553
SWaC	738**	695**	639*
Swyc	186 256 296 .543 .399 .326 510 310 301 .075 .302 .317 580° 566° 511 .038 .044 .074 .277 .184 .259 .360 .548 .394 513 291 347 .073 .335 .246 507 595° 571* .077 .032 .042 057 .000 011 .853 1.000 .972 519 434 .386 .069 .138 .193 072 .121 .230 .814 .694 .450 756** 697** 673* .002 .006 .012 235 165 .023 .440 .590 .940 .075 .117 .045 .807 .702	.019	
SW/aT	749**	687**	642*
Svyi	.003	.009	.018
	199	141	.010
Svyinc	.515	256 .399 310 .302 566 ⁺ .044 .184 .548 291 .335 595 ⁺ .032 .000 1.000 1.000 434 .138 .121 .694 434 .138 .121 .694 697 ⁺⁺ .008 715 ⁺⁺ .008 715 ⁺⁺ .008 165 .590 .117 .702 .225 .460 191 .531 695 ⁺⁺ .008 191 .531 695 ⁺⁺ .008 191 .531 695 ⁺⁺ .008 141 .646	.975

TP/V	857**	836**	809**
wur	.000		.001
WaDtCoaf	071	.121	.230
wgDtCom	.817	836** 0 .000 . 1 .121 . 7 .694 . 0** 715** 2 .006 .	.450
wgDtConfC	769**	715**	673 [*]
C	.002	.006	.012

As can be seen in table 4, the structural metrics and usability quality attributes are significantly but negatively correlated with each other. Communicativeness is negatively correlated to CfWg3, DtNf, DtNfCC, SWgc, SwgT, WdT, WgDtConf. This indicates that in order to increase communicativeness of a feature model, the values of these metrics should be low. Understandability is negatively correlated to CFWg3, CPWg3, DtNfCC, SWgC, SWgT, WdT, WgDTConf. This highlights the fact that increase in the depth and flexibility of configuration decreases the understandability of the feature model. Learnability has negative correlation with CPWg3, DtNf, DtNfCC, SWgC, SWgC, SWgT, WdT, WgDT, WgDtConf. This means that depth, number of features, feature weight and cyclomatic complexity have negative correlation with learnability of a feature model. The learnability will decrease if there is an increase in these metrics.

Metrics indicativeness study shows that the proposed metrics are significantly correlated with usability quality attributes. On this basis, the null hypothesis is rejected because both the variables are significantly correlated with each other. To obtain maximum learnability, understandability and communicativeness of a feature model a balance between the two variables needs to be maintained. Thus the metrics can be used for further analysis.

The correlation study shows that the structural metrics are correlated with the usability sub characteristics. But significant correlation doesn't always guarantee accurate prediction power of the structural metrics. Therefore, regression analysis is done next to study the prediction power of the metrics.

4.3 REGRESSION ANALYSIS

Regression analysis is an equation which represents prediction of a dependent variable from independent variable. This analysis is used when independent variable is correlated with the dependent variable and there is a need to know the predicting power of the independent variable for defining the dependent variables. Regression analysis was done for each of the three sub characteristics of usability.

A. Learnability

The first model was developed to identify strong predictors out of the selected metrics for learnability. The results are shown in table 5.1(i) and 5.1(ii).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimat e		
1	.857ª	.734	.710	.218		
2	.912 ^b	.831	.798	.182		
3	.949°	.901	.868	.147		
	a. Predictors: (Constant), WdT					
b.	b. Predictors: (Constant), WdT, DtConf					
C.	Predictors	s: (Constan RSWgAltN	t), WdT, DtCc land	onf,		

Table 5.1(i). Model Summary of Multiple Regression Analysis

Madal		Unstandardized Coefficients		Standardized Coefficients	т	Sia
	Wodei	В	Std. Error	Beta		Sig.
1	(Constant)	5.992	.239		25.122	.000
I	WdT	344	.063	857	-5.507	.000
	(Constant)	7.251	.560		12.949	.000
1 2 3	WdT	379	.054	943	-6.998	.000
	DtConf	257	.107	324	-2.404	.037
	(Constant)	7.691	.484		15.884	.000
	WdT	466	.056	-1.160	-8.371	.000
3	DtConf	313	.089	394	-3.514	.007
	RSWgAltMa nd	.043	.017	.337	2.524	.033
		a. Deper	ndent Varia	able: Learnability		

Table 5.1(ii). Coefficients

Model Summary across tables 5.1(i) and 5.1(ii) depicts that independent variable viz. WdT, DtConf, RSWgAltMand explains 94.9% of the variability of dependent variable i.e. Learnability. WdT, DtConf collectively explain 91.2% of variability of Learnability and WdT individually explains only 85.7% of variability of Learnability. Rest all variable are excluded due to high level of tolerance. The overall regression model is a good fit for the data. Statistically speaking, the metrics in Model 3 can significantly predict the level of dependent variable learnability.

B. Understandability

The next model was developed for identifying predictors of understandability sub characteristic. The results are contained in table 5.2(i) and 5.2(ii).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	
1	.836 ^a	.699	.671	.411	
2	.914 ^b	.836	.803	.318	
3	.950°	.903	.871	.258	
a. Predictors: (Constant), WdT					
b. Predictors: (Constant), WdT, RSWgAltMand					
c. Predictors: (Constant), WdT, RSWgAltMand,					
			iya		

Table 5.2(i). Model Summary of Multiple Regression Analysis

Madal		Unstandardized Coefficients		Standardized Coefficients	т	Sig		
	WOder	В	Std. Error	Beta	•	olg.		
1	(Constant)	6.939	.450		15.423	.000		
I	WdT	596	.118	836	-5.052	.000		
	(Constant)	7.340	.375		19.582	.000		
2	WdT	787	.113	-1.105	-6.981	.000		
2	RSWgAltM and	.105	.036	.458	2.892	.016		
	(Constant)	7.059	.324		21.793	.000		
	WdT	698	.098	979	-7.105	.000		
3	RSWgAltM and	.118	.030	.518	3.972	.003		
	CPwg3	590	.236	309	-2.496	.034		
	a. Dependent Variable: Understandability							

Table 5.2(ii). Coefficients

Various values across tables 5.2(i) and 5.2(ii) indicate positive results. The adjusted R square value of model 3 is . 950, which indicates that 95% of the variance can be indicated by using this linear regression model. The model with indicators viz. WdT, RSWgAltMand, CPwg3 has high significance thus can be used for prediction. Out of these three metrics Wdt and CPWg3 have negative effect whereas RsWdAltmand has positive effect while predicting understandability. As a conclusion of this model it can be said that Wdt, RSWgAltmand and CPWg3 can be used to form regression equation in order to calculate understandability.

C. Communicativeness:

The last analysis was done keeping in mind learnability of feature models with the help of designed metrics. The results are contained in table 5.3(i) and 5.3(i).

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate				
1	.809 ^a	.655	.623	.488				
2	.887 ^b	.786	.744	.402				
a. Predictors: (Constant), WdT								
b. Predictors: (Constant), WdT, RSWgAltMand								

Table 5 3(i)	Model Summar	v of Multiple Rear	ession Analysis
	Model Ourrinal	y or muniple riegr	

Model		Unstandardized Coefficients		Standard ized Coefficie nts	т	Sig.	
		В	Std. Error	Beta			
1	(Constant)	7.157	.534		13.393	.000	
	WdT	639	.140	809	-4.565	.001	
2	(Constant)	7.593	.475		16.001	.000	
	WdT	848	.143	-1.073	-5.937	.000	
	RSWgAltM and	.114	.046	.449	2.483	.032	
a. Dependent Variable: Communicativeness							

Tables 5.3(i) and 5.3(ii) show the regression values for communicativeness. The adjusted R square for communicativeness is 78.6% which is fairly satisfactory. The models consists two metrics WdT, RSWgAltMand. In the second model WdT has negative value and RSWgAltMand has positive value. Communicativeness can be thus predicted or explained with the help of these two equations.

On the basis of various values obtained and various models designed it is concluded that out of the proposed metrics Wdt, dtConf, RsWgAltMand and CPWg3 have turned out to be strong predictors of usability sub characteristics. Out of them, interestingly Wdt, CPWg3 also had strong degree of correlation with usability sub characteristics.

Based on the models build following equations are developed to calculate values of usability sub characteristics:

- 1. L = 7.691-0.466(WdT) 0.313(DtConf) + 0.043(RSWgAltMand)
- 2. U = 7.059-0.698(WdT) + 0.118(RSWgAltMand) 0.590(CPWg3)
- 3. C = 7.593 0.848(WdT) + 0.114(RSWgAltMand)

Summary of Analysis

On the basis of the various results obtained, we conclude that the designed structural metrics are significantly correlated with usability sub characteristics. Using these structural metrics linear regression equation based models can be built for predicting each sub characteristic of usability.

5- CONCLUSION

5.1 THREATS TO VALIDITY

Construct validity is the degree to which the variables are accurately measured during the experiment using correct measurement instruments. The independent variables were validated in a previous study. The dependent variable is measured on 7 point Likert scale providing best number of options to the participants. We have also applied valid reliability test to check the reliability of the same.

Internal Validity: The internal validity is the degree of confidence about the cause- effect relationship i.e. what are the factors of interest and what results have been obtained. An internally invalid experiment will lead to irrelevant results from the point of view of a causal relationship. In our case the analysis is based on correlation. Also there was no difference between the subjects i.e. they all were from the computer science discipline. Feature models were selected keeping in mind various domains of the real life. The participants were provided enough time to understand and become familiar with the task. The time duration of the experiment was also short. Plagiarism was also taken care of.

External Validity: This validity is the extent up to what level the results can be generalized to the population under study and also other scenarios of real life. In our case we tried to include feature models which were best fitting in size and covering a wide domain. We have included students who are from computer science domain only. However in our further experiments we will involve professionals and educationist to strengthen this validity.

5.2 CONCLUDING REMARKS

Various statistical tests were applied to study the relation between the structural metrics and SPL feature models. The structural metrics are significantly correlated with usability sub characteristics. On the basis of this result, further analysis is done. Linear regression equation based models are built using these metrics. Nearly all models predicted SPL feature model usability with the help of the structural metrics. Therefore the research concludes that the proposed set of metrics is accurately predicting feature model usability. Therefore, feature model usability can be accurately

estimated using the designed set of structural metrics. In the future the prediction models can be sued to test large test sets and predict usability of feature models.

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