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, alternative: 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.

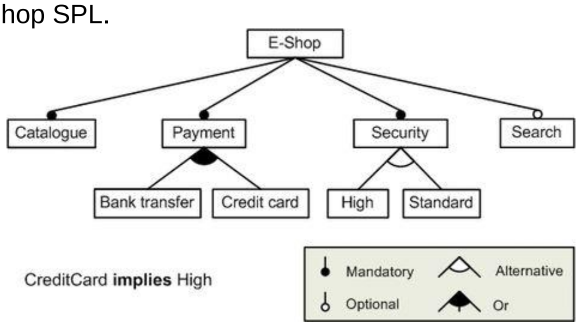

Figure 1. Sample feature mode of E-shop

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

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

Table 1. Description of the Designed Structural Metrics

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

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.

Table 2. GQM to Set the Experimental Goal

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

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 H_0: 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**
.933	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.

Table 4. Metrics Indicativeness

	Learnability	Understandability	Communicativeness
TF	-.010	.127	.120
	.974	.679	.696
CPf	-.433	-.321	-.309

	.139	.285	.304
CAltOpt	-.326	-.228	-.276
	.276	.454	.361
CFWg1	-.186	-.256	-.296
	.543	.399	.326
CFWg2	-.510	-.310	-.301
	.075	.302	.317
CFWg3	-.580*	-.566*	-.511
	.038	.044	.074
CPWg1	.277	.184	.259
	.360	.548	.394
CPwg2	-.513	-.291	-.347
	.073	.335	.246
CPwg3	-.507	-.595*	-.571*
	.077	.032	.042
CStOptF	-.057	.000	-.011
	.853	1.000	.972
CStAltF	-.519	-.434	-.386
	.069	.138	.193
DtConf	-.072	.121	.230
	.814	.694	.450
DtNf	-.756**	-.697**	-.671*
	.003	.008	.012
DtNfCC	-.769**	-.715**	-.673*
	.002	.006	.012
MSWgSt	-.235	-.165	-.023
	.440	.590	.940
RCPC	.075	.117	.045
	.807	.702	.884
RSWgOptMand	.062	.225	.219
	.840	.460	.472
RSWgAltMand	-.359	-.191	-.181
	.229	.531	.553
SWgC	-.738**	-.695**	-.639*
	.004	.008	.019
SWgT	-.749**	-.687**	-.642*
	.003	.009	.018
SWgTHC	-.199	-.141	.010
	.515	.646	.975

WdT	-.857**	-.836**	-.809**
	.000	.000	.001
WgDtConf	-.071	.121	.230
	.817	.694	.450
wgDtConfCC	-.769**	-.715**	-.673*
	.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, 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).

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

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.857[a]	.734	.710	.218
2	.912[b]	.831	.798	.182
3	.949[c]	.901	.868	.147
a. Predictors: (Constant), WdT				
b. Predictors: (Constant), WdT, DtConf				
c. Predictors: (Constant), WdT, DtConf, RSWgAltMand				

Table 5.1(ii). Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.992	.239		25.122	.000
	WdT	-.344	.063	-.857	-5.507	.000
2	(Constant)	7.251	.560		12.949	.000
	WdT	-.379	.054	-.943	-6.998	.000
	DtConf	-.257	.107	-.324	-2.404	.037
3	(Constant)	7.691	.484		15.884	.000
	WdT	-.466	.056	-1.160	-8.371	.000
	DtConf	-.313	.089	-.394	-3.514	.007
	RSWgAltMand	.043	.017	.337	2.524	.033
a. Dependent Variable: Learnability						

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).

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

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[c]	.903	.871	.258
a. Predictors: (Constant), WdT				
b. Predictors: (Constant), WdT, RSWgAltMand				
c. Predictors: (Constant), WdT, RSWgAltMand, CPwg3				

Table 5.2(ii). Coefficients

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

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(ii).

Table 5.3(i). Model Summary of Multiple Regression Analysis

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(ii). Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	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
	RSWgAltMand	.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.

REFERENCES

[1] McGregor, J.D., Muthig, D., Yoshimura, K. and Jensen, P., 2010. Guest editors' introduction: Successful software product line practices. IEEE Software, 27(3).

[2] Clements, P.C., 2015, October. Product Line Engineering Comes to the Industrial Mainstream. In INCOSE International Symposium (Vol. 25, No. 1, pp. 1305-1319).

[3] Pohl, K., Böckle, G. and van Der Linden, F.J., 2005. Software product line engineering: foundations, principles and techniques. Springer Science & Business Media.

[4] Weiss, D.M., Clements, P.C., Kang, K. and Krueger, C., 2006, August. Software product line hall of fame. In Software Product Line Conference, 2006 10th International (pp. 237-237). IEEE.

[5] Lee, K., Kang, K. and Lee, J., 2002. Concepts and guidelines of feature modeling for product line software engineering. Software Reuse: Methods, Techniques, and Tools, pp.62-77.

[6] Kang, K.C., Cohen, S.G., Hess, J.A., Novak, W.E. and Peterson, A.S., 1990. Feature-oriented domain analysis (FODA) feasibility study (No. CMU/SEI-90-TR-21). Carnegie-Mellon Univ Pittsburgh Pa Software Engineering Inst.

[7] Czarnecki, K., Helsen, S. and Eisenecker, U., 2005. Formalizing cardinality-based feature models and their specialization. Software process: Improvement and practice, 10(1), pp.7-29.

[8] Poels, G. and Dedene, G., 2000. Distance-based software measurement: necessary and sufficient properties for software measures. Information and Software Technology, 42(1), pp.35-46.

[9] Fenton, N., 1994. Software measurement: A necessary scientific basis. IEEE Transactions on software engineering, 20(3), pp.199-206.

[10] Briand, L., S. Morasca, S.,and V.R. Basili, 1994. Defining and validating high-level design metrics.

[11] Chidamber, S.R. and Kemerer, C.F., 1994. A metrics suite for object oriented design. IEEE Transactions on software engineering, 20(6), pp.476-493.

[12] Lorenz, M. and Kidd, J., 1994. Object-oriented software metrics: a practical guide. Prentice-Hall, Inc..

[13] Harrison, R., Counsell, S.J. and Nithi, R.V., 1998. An evaluation of the MOOD set of object-oriented software metrics. IEEE Transactions on Software Engineering, 24(6), pp.491-496.

[14] Genero, M., Olivas, J., Piattini, M. and Romero, F., 2001, June. Using metrics to predict OO information systems maintainability. In International Conference on Advanced Information Systems Engineering (pp. 388-401). Springer, Berlin, Heidelberg.

[15] Bansiya, J. and Davis, C.G., 2002. A hierarchical model for object-oriented design quality assessment. IEEE Transactions on software engineering, 28(1), pp.4-17.

[16] Manso, M., Genero, M. and Piattini, M., 2003. No-redundant metrics for UML class diagram structural complexity. In Advanced Information Systems Engineering (pp. 1029-1029). Springer Berlin/Heidelberg.

[17] Cruz-Lemus, J.A., Maes, A., Genero, M., Poels, G. and Piattini, M., 2010. The impact of structural complexity on the understandability of UML statechart diagrams. Information Sciences, 180(11), pp.2209-2220.

[18] Bagheri, E. and Gasevic, D., 2011. Assessing the maintainability of software product line feature models using structural metrics. Software Quality Journal, 19(3), pp.579-612.

[19] Fernández-Sáez, A.M., Genero, M. and Chaudron, M.R., 2013. Empirical studies concerning the maintenance of UML diagrams and their use in the maintenance of code: A systematic mapping study. Information and Software Technology, 55(7), pp.1119-1142.

[20] Goel, B.M. and Bhatia, P.K., 2013. Analysis of reusability of object-oriented systems using object-oriented metrics. ACM SIGSOFT Software Engineering Notes, 38(4), pp.1-5.

[21] Huda, M., Arya, Y.D.S. and Khan, M.H., 2015. Metric Based Testability Estimation Model for Object Oriented Design: Quality Perspective. Journal of Software Engineering and Applications, 8(04), p.234.

[22] Samir, A. and Darwish, N.R., 2016. Reusability Quality Attributes and Metrics of SaaS from Perspective of Business and Provider. International Journal of Computer Science and Information Security, 14(3), p.295.

[23] Sascha El-Sharkawy, Nozomi Yamagishi-Eichler, and Klaus Schmid. Implementation Metrics for Software Product Lines - A Systematic Literature Review. Report No. 1/2017, SSE 1/17/E, 2017.

[24] Vyas G. and Sharma A., (2016) “Empirical Evaluation of Metrics to Assess , Software , roduct Line Feature Model Usability”, IJCSET International

Journal of Computer Science Engineering and Technology (IJCSET), Volume 6, Issue 2, Page no 82-88, February 2016 , ISSN: 2231-0711.

[25] Basili, V.R., 1992. Software modeling and measurement: the Goal/Question/Metric paradigm.

[26] Kitchenham, Barbara, and Shari Lawrence Pfleeger. "Software quality: the elusive target [special issues section]." IEEE software 13, no. 1 (1996): 12-21.

[27] Barbacci, M., Klein, M.H., Longstaff, T.A. and Weinstock, C.B., 1995. Quality Attributes (No. CMU/SEI-95-TR-021). CARNEGIE-MELLON UNIV PITTSBURGH PA SOFTWARE ENGINEERING INST.

[28] Fey, D., Fajta, R. and Boros, A., 2002, August. Feature modeling: A meta-model to enhance usability and usefulness. In International Conference on Software Product Lines (pp. 198-216). Springer Berlin Heidelberg.

[29] Al-Kilidar, H., Cox, K. and Kitchenham, B., 2005, November. The use and usefulness of the ISO/IEC9126 quality standard. In Empirical Software Engineering, 2005. 2005 International Symposium on (pp. 7-pp). IEEE.

[30] Mendonca, M., Branco, M. and Cowan, D., 2009, October. SPLOT: software product lines online tools. In Proceedings of the 24th ACM SIGPLAN conference companion on Object oriented programming systems languages and applications (pp. 761-762). ACM.