Improving Learning ManagementSystem using Data Mining

Ms.Supriya Solaskar
M.E Student
St. Francis Institute of Technology,
Mumbai University,
Mumbai- 400103. India

Ms. Anuradha. G
Associate Professor
St. Francis Institute of Technology,
Mumbai University,
Mumbai- 400103. India

Dr. A. K. Sen
Principal
St. Francis Institute of Technology,
Mumbai University,
Mumbai-400103. India

Abstract- **In the last decade, the effect of internet usage in education has increased tremendously and student's learning skills seems to have improved through these emerging technologies. The use of Learning Management System (LMS) emerges as a great opportunity to improve and complement teaching and learning, by encouraging students to perform different activities. LMS caters to the needs and usability of both the types of users- faculty/teachers, students. On one hand it supports teachers in creating, administrating and managing online course. On the other hand, LMS treats all students/learners equally, regardless of their personal abilities to study. The proposed work uses a fuzzy inference system (FIS) which recommends a learning material based on student's learning styles and teaching evaluation. The goal is to enhance an existing Learning Management System by delivering course material that best fits student's learning styles.**

Keywords—Learning Management System (LMS), Learning Styles, fuzzy system

I. INTRODUCTION

A Learning Management System (LMS) is a tool for delivering, tracking andmanaging training/education [1].Some commercial LMS have been developed such as Blackboard, WebCT and Top-Class [3] while some examples of open source systems are ATutor, OLAT, Sakai and Moodle.

LMSs range from systems for managing training/educational records to software for distributing courses over the Internet and offering features for online collaboration [1]. Some corporate training departments purchase LMSs to automate record-keeping as well as the registration of employees for classroom and online courses [1].

Most LMSs are web-based to facilitate access to learning content and administration. LMSs are used by educational institutions for classroom teaching and offering courses to larger population of learners across the world.

Teachers use an LMS to develop web-based course notes and quizzes, to communicate with students using forums and chats. Students use it for accessing the course material, learning, communication, and collaboration.

The existing LMSs present same course material to all learners based on the "one-size-fits-all" concept. However, every learners individual needs, characteristics and learning abilities might be different. Learning characteristics might mainly cater to prior subjective knowledge, cognitive abilities, learning styles. These individual learning differences affect the learning process and are the reason why some learners find it easy to learn in a particular course, whereas others find the same course difficult. The mismatch between students learning style and the course material provided by LMS, affects the students learning process. It will be very useful if the system recommend learning material taking into consideration the learning styles that will improve the learning.

The rest of the paper is organized as follows: Section II focuses on related work, followed by proposed solution in section III. Implementation details and results are shown in section IV whereas section V is analysis of the work. Finally Conclusion and future work in section VI.

II. RELATED WORK

In the last few years, researchers have begun to investigate various data mining methods to help instructors and administrators to improve e-learning systems

In [2], the authors have presented a general and up-to-date survey on Data Mining application in e-learning. They provided a taxonomy of e-learning problems to which Data Mining techniques have been applied, including, for instance: Students' classification based on their learning performance; detection of irregular learning behaviors; e-learning system navigation and interaction optimization; clustering according to similar e-learning system usage; and systems' adaptability to students' requirements and capacities.

Authors also described the main data mining techniques used, such as statistics, classification, clustering and association rule mining of Moodle data.

A lot of research has been done on identifying learning styles**.** Felder and Silverman describe thelearning styles of the learners as shown in table 1.

Felder and Soloman developed Index of Learning Styles (ILS), a 44-item questionnaire for identifying the learning styles according to FSLSM [8].The questionnaire proposes a list of items effective in identify the style of each learner.

The resulting index of preference for each dimension is expressed by an odd integer ranging [-11, +11] since 11 questions are posed for each of the four dimensions. For each question 2 possible answers are available, the one with value +1, the other with value -1. As an example, when answering a question with an active preference, the learner's score is incremented by +1 while for reflective preference the score is decreased by 1 (i.e. -1 is added) [7,8].

Some recent research deals with identifying learning styles from the behavior of learners. Graf and Kinshuk [9] detect learning styles based on the behavior of learners during an on-line course.

Some research has been done on adapting a course material based on learning styles.

The authors [10] described method for course adaptation which is based on using data mining techniques to classify students into clusters with regards to Felder Silverman learning styles model.

Romero et al. [11] described a personalized recommender system that uses web mining techniques for recommending a student which (next) links to visit within an adaptable educational hypermedia system AHA! Adaptive learning allows the learner to access the most appropriate, interesting and challenging learning activities.

Table1: FSLSM Model

Based on how learners process information	Active	Prefer to work in a group, trying things out
	Reflective	Prefer to work alone or in a small group. They think about the learned material unlike active learners
Based on how learners perceive information	Sensitive	Prefer concrete, facts and practical information. They like to solve the problems
	Intuitive	Prefer to learn abstract material, theories and its underlying meanings
Based on how learners receive information	Visual	Prefer visually pleasing material such as graphs, flowcharts, diagrams, videos etc.
	Verbal	Prefer textual representation regardless of whether its written or spoken
Based on how learners understand information	Sequential	Learn in small incremental steps, interested in details
	Global	Learn in large leaps, more interested in overviews.

Fuzzy association rules have been used in a personalized e-learning material recommender system. The authors developed a framework for personalized learning recommender systems (PLRS). The approach of fuzzy matching rules is used for finding recommended learning materials based on student requirement [12].

Herman Surjono[13] designed adaptive e-learning system for presenting learning material based on two learning style models. These models are VAK (visual, auditory and kinesthetic) and Felder. The author presented learning material for Global-Sequential learners with variations of VAK.

III. PROPOSED WORK

Figure 1 shows the proposed solution which includes designing a Fuzzy Inference System for recommending learning material.

Following are the inputs to FIS -
1. Learning Styles
2. *Teaching Evaluation*

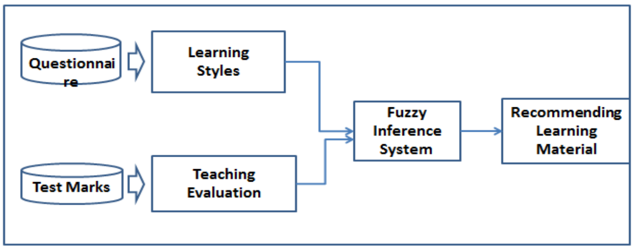


Fig.1 Proposed System for Recommending Learning Material

Input and output variables are described along with their membership functions.

Input variables are:

1. Learning Styles

The learning styles of students were identified through the questionnaire developed by Felder and Soloman [8]. The questionnaire contains list of questions based on each learning style. The learning styles of the students were identified and stored in the database as per the questionnaire. Students were categorized based on the learning styles. Initially a generalized study material which caters to all types of learners were provided. For example, videos were provided for visual learners, audio recordings, pdf and lecture notes were provided for verbal learners. The fuzzy inference system is then devised using the learning styles and the evaluation as inputs and deciding on the type of material which has to be modified for individual student.

Fig. 2 shows the membership function plots for learning styles. As there are 44 questions, learning style can take numbers in the interval [0, 44] as its value.

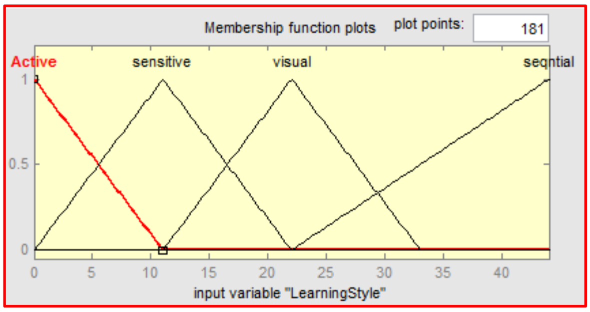


Fig.2 Membership plot for Input-Learning Styles

The Learning styles are divided into linguistic variables namely Active, Sensitive, Visual and Sequential. Membership functions are then formed assigning the proper range to respective linguistic variables.

Learning styles with its values are shown in Table 3.

Table 2: Classification of Learning Styles

Input	Range	Fuzzy Set
Learning Styles	< 11	Active
	< 22	Sensitive
	11-33	Visual
	22-44	Sequential

In this paper, triangular membership function for converting the crisp set into fuzzy set is used. Membership value of the input variable of learning styles are assigned as per the membership value computations given in equation (1):

$$\mu_{active}(x) = \frac{11-x}{11} \; ; 0<x \le 11$$

$$\mu_{sensietiv}(x) = \begin{Bmatrix} \frac{x}{11} & ; 0 < x \le 11 \\ \frac{22-x}{11} & ; 11 < x \le 22 \end{Bmatrix}$$

$$\mu_{visual}(x) = \begin{Bmatrix} \frac{x-11}{11} & ; 11 < x \le 22 \\ \frac{33-x}{11} & ; 22 < x \le 33 \end{Bmatrix}$$

$$\mu_{sequential}(x) = \left\{ \frac{x-22}{22} \; ; \quad 22 < x \le 44 \right\} \ldots\ldots\ldots\ldots(1)$$

2. TEACHING EVALUATION

Initially all the students were provided with same learning material for each module and a test was conducted.
From the test results students were categorized into four categories namely fail, average, good and excellent.
The membership functions for teaching evaluation are shown in fig.3
The test was evaluated out of hundred hence the input takes the value in the range of [0,100].

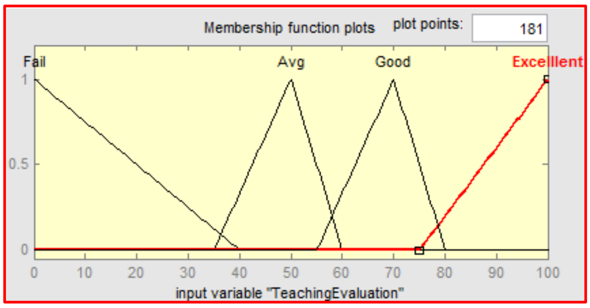


Fig. 3 Membership plot for Input-Teaching Evaluation

Teaching evaluation field has four fuzzy sets. These fuzzy sets have been shown in Table 3

Table3: Classification of Teaching Evaluation

Input	Range	Fuzzy Set
Teaching Evaluation	< 40	Fail
	35-60	Average
	55-80	Good
	80-100	Excellent

The triangular membership function expression for each set is as shown below:

$$\mu_{Fail}(y) = \left\{ \frac{40-y}{40} \; ; 0 < y \le 40 \right\}$$

$$\mu_{Average}(y) = \begin{Bmatrix} \frac{y-35}{15} & ; 35 < y \le 50 \\ \frac{60-y}{10} & ; 50 < y \le 60 \end{Bmatrix}$$

$$\mu_{Good}(y) = \begin{Bmatrix} \frac{y-55}{15} & ; 55 < y \le 70 \\ \frac{80-y}{10} & ; 70 < y \le 80 \end{Bmatrix}$$

$$\mu_{Excellent}(y) = \left\{ \frac{y-75}{25} \; ; 75 < y \le 100 \right\} \ldots\ldots\ldots\ldots(2)$$

Based on the above two inputs rule base can be generated.

3. OUTPUT VARIABLE

The output variable is the recommended learning material, which has four linguistic variables.
The membership plot for output is shown in Fig.4

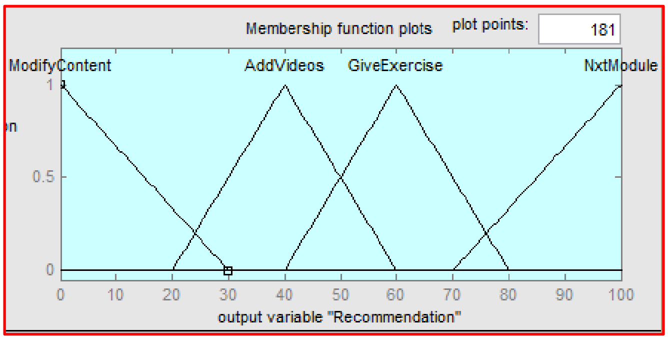


Fig. 4 Membership plot for Input-Teaching Evaluation

Table 4 shows all variables with their ranges.

Table 4: Classification of Output

Output	Range	Fuzzy Set
Recommendation	< 30	Modify Content
	20-60	Add Videos
	40-80	Give Exercise
	70-100	Next Module

Fuzzy Inference System

Fuzzy Inference System is the most important modeling tool based on fuzzy set theory. To design a fuzzy system, input variable and output variable should be described as a fuzzy variable. A fuzzy system based on Mamdani model is designed.

Triangular function: The triangular curve is a function of a vector, x, and depends on three scalar parameters *a*, *b*, and *c*, as given by-

$$f(x;a,b,c)=max(min\left(\left(\frac{x-a}{b-a}\right),\left(\frac{c-x}{c-b}\right),0\right) \quad ....(3)$$

The process of taking an input (e.g. Marks) and processing it through a membership function to determine the linguistic variables (e.g. Fail, Average, etc.) is called fuzzification .

Fuzzy Rules

Fuzzy inference system consists of if–then rules that specify a relationship between the input and output fuzzy variables. The designed system includes 16 rules.
Table 5 shows the fuzzy rule base.

Table 5: Rules for the fuzzy system

Grade	Active	Sequential	Visual	Sensitive
Fail	Modify Content	Modify Content	Add videos	Modify content
Average	Modify Content	Modify content	Add videos	Modify content
Good	Give exercise	Give exercise	Give exercise	Give exercise
Excellent	Next Module	Next Module	Next Module	Next Module

The sample formulation of rules would be like

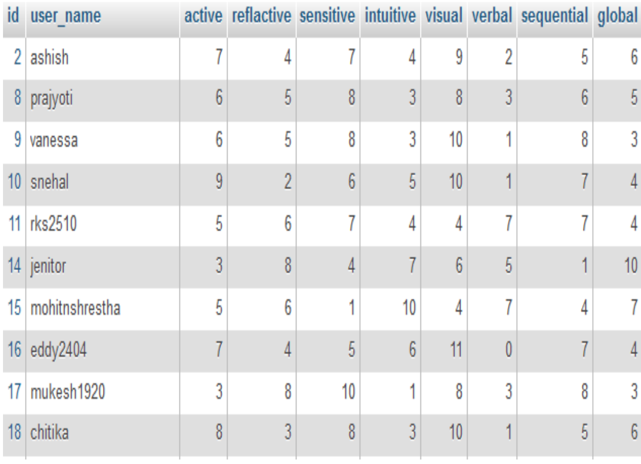
If Learning Style is Visual and Teaching evaluation is failed then recommendation is add videos

If Learning Style is Visual and Teaching evaluation is Good then recommendation is give
Exercise.

The recommendation is performed using the MAX MIN method and fuzzy rules.

IV. IMPLEMENTATION AND RESULTS

The study was conducted on 74 students of third year computer engineering. The students were given course material of five subjects such as web technologies, operating systems, microprocessor, computer networks and object oriented analysis and design. The tests for different subjects were conducted by the respective subject teachers. The system is developed by using PHP as front end and MySQL as backend with Apache server.
Students' profiles that include the learning style are stored in a MySQL database as shown in fig.5



id	user_name	active	reflactive	sensitive	intuitive	visual	verbal	sequential	global
2	ashish	7	4	7	4	9	2	5	6
8	prajyoti	6	5	8	3	8	3	6	5
9	vanessa	6	5	8	3	10	1	8	3
10	snehal	9	2	6	5	10	1	7	4
11	rks2510	5	6	7	4	4	7	7	4
14	jenitor	3	8	4	7	6	5	1	10
15	mohitnshrestha	5	6	1	10	4	7	4	7
16	eddy2404	7	4	5	6	11	0	7	4
17	mukesh1920	3	8	10	1	8	3	8	3
18	chitika	8	3	8	3	10	1	5	6

Fig.5: Database storing Questionnaire answers

The designed system has three users namely Administrator, Students and Teachers. Each described briefly as follows:

Administrator Module

In order to use the system, students and teachers have to register and enrol themselves for a course. The details are sent to admin for verification .Once the verification is done, users get an access to the system.

Student Module

After enrolling to a course students were provided with a Felder-Silverman questionnaire. The students can't access the learning material unless they fill out the questionnaire. Once the learning style is identified, student get access to the learning material. The students can download ppts, videos and other learning material.

Teacher Module

The designed system allows teachers to upload course material in various formats like ppt, audios, videos, pdfs, etc. A teacher can upload learning material based on learning styles.
As shown in fig. 6, if teacher selects 'visual' it means that the learning material is visible to the learners having learning style as 'visual'.

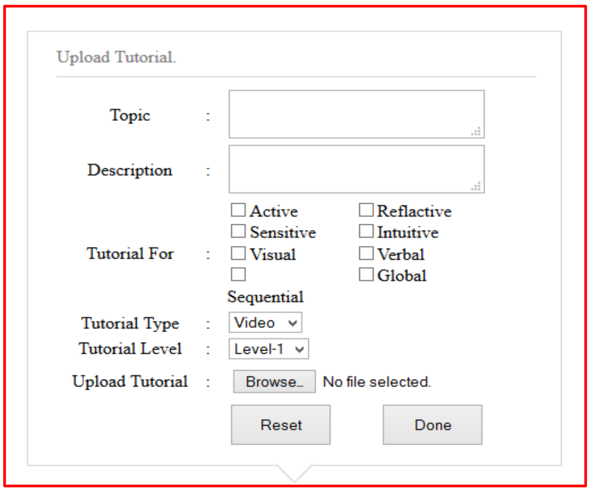


Fig.6 Upload Tutorial Window

The details include learning style of a student, marks of different tests and recommended learning material after each test.
Fig.7 shows the recommended learning material after test 1 and test2 for same subject.

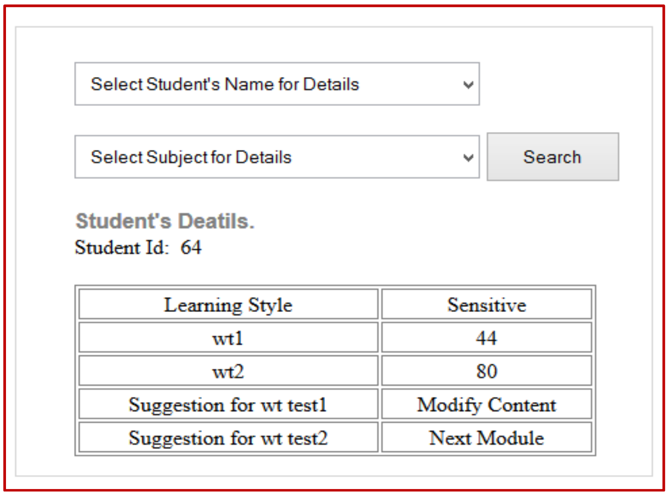


Fig.7 Output : Recommended Learning Material

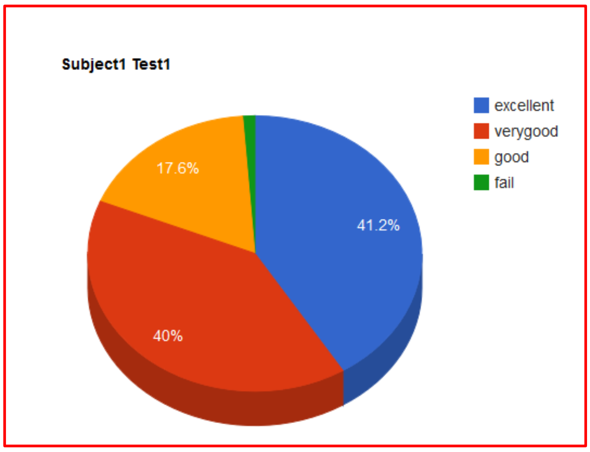
V. ANALYSIS

Table 5 shows the number of students belonging to different learning styles. It is observed that most of the students are visual learners

Table 5: Identified Learning Styles

	Learning Style	Number of Students
1	Active	6
	Reflective	1
2	Sensitive	16
	Intuitive	2
3	Visual	31
	Verbal	2
4	Sequential	5
	Global	2

The pie charts shown in the fig. 8 represent the performance of students in each test.



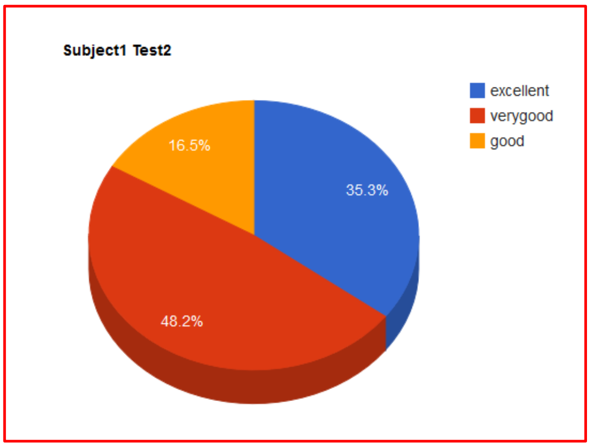


Fig.8 Pie-charts showing students performance

Likewise pie-charts can be generated for other subjects. The table 6 shows student's performance in different subjects in all four categories. From table it can be seen that the number of students belonging to failed and good category has decreased whereas number of students belonging to very good category has increased.

Table[6]:Students Performance

Subject	Test	Percentage of students in each Group			
		Excellent	Very Good	Good	Fail
WT	1	41.2	40	17.6	1.2
	2	35.3	48.2	16.5	0
CN	1	9.4	47.1	37.6	5.9
	2	14.1	56.5	28.2	1.2
OS	1	17.6	43.5	34.1	4.7
	2	5.9	58.8	29.4	5.9
OO	1	4.7	27.1	45.9	22.4
	2	3.5	43.5	41.2	11.8
MP	1	7.1	44.7	24.7	23.5
	2	9.4	38.8	34.1	17.6

Fig. 9 and fig.10 graphically demonstrates the subject wise performance of students in two tests from table.

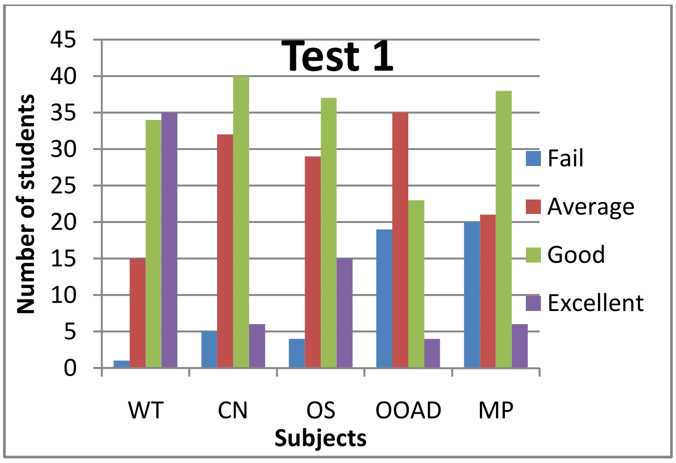


Fig.9: Students performance in Test1

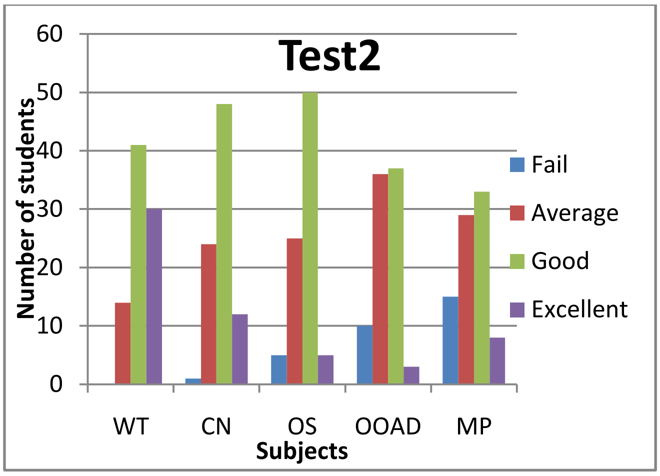


Fig.10: Students performance in Test2

Comparing the results from above graphs it can be pointed out that Test2 gives us better results after providing learning material as per their learning styles. Thus the devised system helps to improve the learning process of the student by considering their personal needs and learning abilities.

VI CONCLUSION

Learning is different for each student; therefore, the student's differences and learning styles should be considered in education systems.

This proposed work includes a mechanism for recommending learning material to students according to their needs. At the same time, allows teachers to refine the material provided to students based on their learning skills.

Future work includes considering more parameters for recommending learning material.

REFERENCES

1. Oneto.LAbel.F, Herder.E, Smits.D, "Making Today's Learning Management Systems Adaptive", *Learning in the Synergy of Multiple Disciplines, Proceedings of the EC-TEL 2009, volume 5794 of Lecture Notes in Computer Science, Springer, October 2009*
2. Castro. F, Vellido .A,Nebot. A and Mugica.F, "Applying Data Mining Techniques to e-Learning Problems",*Evolution of Teaching and Learning Paradigms in Intelligent EnvironmentStudies in Computational Intelligence* , Volume 62, pp 1 17, 2007.
3. Romero. C, Ventura. S and Garcia. E, "Data mining in course management systems: Moodle case study and tutorial", *Computer and Education*, Volume 51, August 2008.
4. Aydin. C, Tirkes. G "Open Source Learning Management Systems in E-Learning and Moodle", IEEE EDUCON *Education Engineering*, pp 593-600, 2010.
5. Felder.R, Silverman.L,"Learning and Teaching Styles in Engineering Education" *Engineering education*, 1988.
6. Felder.R, "Learning and Teaching Styles in Engineering Education", 2002
7. Silvia Rita .V, Sabine.G.,Kinshuk, Tommaso.L, "Analysis of Felder-Silverman Index of Learning Styles by a Data-driven Statistical Approach" , 2002.
8. http://www.engr.ncsu.edu/learningstyles/ilsweb.html, "ILS Questionnaire", October 2013.
9. Graf, S. and Kinshuk, " An approach for detecting learning styles in learning management systems". in*international conference on advances learning technologies (ICALT 06),* 2006.
10. Despotovic-Zrakic.M,Markovic.A, Bogdanovic.Z ,Barac.D and Krco.S , "Providing Adaptivity in Moodle LMS Courses*", Educational Technology & Society*, v15, pp 326–338,2012
11. Romero.C, Ventura.S ,Delgado.J.A , Bra .P.D, "Personalized Links Recommendation Based on Data Mining in Adaptive Educational Hypermedia Systems" pp. 292–306, 2007.
12. Lu. J, "Personalized E-learning Material Recommender System",In: *Proceedings of International Conference on Information Technology for Application*, pp. 374–379 ,2004
13. Surjeno.H, "The Design of Adaptive E-Learning Systems Based on Student's Learning Styles"*Journal of Computer Science and Information Technologies*, Vol. 2 (5) , 2011, 2350-2353