Intelligent Computing Methods in E-Learning Environment

A

Thesis

Submitted to

LOVELY PROFESSIONAL UNIVERSITY

For the award of

DOCTOR OF PHILOSOPHY (Ph.D)

in

(COMPUTER SCIENCE AND ENGINEERING)

By

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2017

Candidate's Declaration

I, **Aditya Khamparia**, certify that the work embodied in the Ph.D. thesis is my own bonafide work carried out by me under the supervision of **Dr. Babita Pandey** for a period of 4 years 02 months from July 2013 to Sep 2017 at School of Computer Science and Engineering, Lovely Professional University, Phagwara, India. The matter embodied in this Ph.D. thesis has not been submitted for the award of any other degree/diploma.

I declare that I have faithfully acknowledged, given credit to and referred to the research workers wherever their works have been cited in the text and the body of the thesis. I further certify that I have not willfully lifted up some other's work, para, text etc. reported in the journals, books, magazines etc. or available at websites and included them in this Ph.D. thesis and cited as my own work.

Date: **Aditya Khamparia**

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<u>Supervisor Certificate</u>

This is to certify that the work reported in the Ph.D. thesis entitled "**Intelligent Computing Methods in E-Learning Environment"**, submitted by **Aditya Khamparia** at **Lovely Professional University, Phagwara, India** is a bonafide record of his original work carried out under my supervision. This work has not been submitted elsewhere for any other degree and is correct to the best of my knowledge.

Date: Signature of Supervisor

(Dr. Babita Pandey)

Abstract

This is an era of E-learning. With the invent of World Wide Web (WWW) technologies paradigm of educational based learning has been shifted from teacher centered to learner centered and provide dynamic course material content to learner according to their needs and preferences. Earlier learner in conventional classroom teaching suffers from following the fixed sequence to cover the course from textbook irrespective of their personality and background experiences. E-learning provides opportunities for people of all ages to take course online at anytime and anywhere. Most of the learning material available in the web is static due to which accessing and selection of appropriate learning material becomes a time-consuming process.

Due to lack of an inappropriate course content sequencing, classification, categorization and prediction of learner on the basis of their performance and providing security to E-learning system by removing threats there is a need to develop an intelligent computing method based E-learning system that integrate soft computing and probabilistic based techniques like Artificial Neural Network (ANN), Data Mining (DM), Case based Reasoning (CBR), Hidden Markov Model (HMM) and Petri nets with usage of forward hidden states, security metrics, psychological and cognitive parameters for providing adaptive learning content according to learner interest, goal, preferences and skills.

The main objective of the thesis is to reduce learning cost, provide flexible course delivery according to learner characteristics and behavior, gathers more efficient approaches for learning activities such as learning path sequencing, object recommendation and optimization of course delivery with the help of intelligent computing techniques which improve performance of learner. The thesis has been divided into eight chapters. A literature review of some reported work on E-learning from four perspectives: Intelligent soft computing methods in E-learning, Semantic Web and Ontology based services, Hidden markov model and petri net based modeling for E-learning has been performed in Chapter 1.

Basic concepts pertaining to Data mining, Case Based Reasoning and ANN methods (Decision tree, Neural networks, Cases), Hidden Markov Model (HMM) with its application and usage in E-learning systems, Petri nets and their usages in security based e-learning system, and Semantic web technology with ontology and web services has been given in Chapter 2.

Chapter 3 presents an adaptive CBR-ANN-DM based integrated method to provide learning material to student according to their needs and student features at different levels of programming in computer science. This method has been deployed for the learning of C Programming language. In this method various student features like Gender, Personality, Anxiety, Learning Style and Cognitive Parameters have been taken into consideration for adaptive content delivery to individual learner. This chapter describes the use of data mining and ANN methods for classification and categorization of learning content. ANN methods help in categorization and prediction of student features on basis of their performance. A novel feature of case based reasoning is involved to represent the attribute value pairs of student features as cases in case base.

Chapter 4 and Chapter 5 presents a Hidden Markov Model (HMM) based E-learning system which describes its two common perspectives: To develop an adaptive web based educational system using HMM for computer programming and to improve the learning performance of learners by predicting their Psychological (P) and Environmental (E) factors which enhances their learning productivity. In the proposed approach an adaptive web based e-learning system based on HMM approach which predicts the future actions and next lecture content of C programming to be visited by student based on history of lecture contents and delivers the learning material according to their ability and preferences. In HMM model grade prediction of learner based on their P and E factors have been used which suggests the complementary positive factors with respect to negative factor so that the performance of learner can improve.

Chapter 6 presents a threat driven security framework using petri nets to remove the design vulnerabilities in system. The modified threat driven framework measures the correctness, soundness and completeness of the Stochastic Petri Nets (SPN) and Aspect Oriented Stochastic Petri Nets (AOSPN) models. Threat analysis (risk assessment), disintegration correction assessment, mitigation (attenuation) correction assessment and mitigation (attenuation) assessment are introduced phases that were added to threat modeling framework. By using base, temporal and environmental security metrics, it has been observed that after applying threat mitigations when security metric is computed it come down to 2.3 from 4.3 before applying mitigations.

Performance evaluation of the integrated model is presented in Chapter 7. First step consists of computing the importance of Learning problem (LPI) and measurement (LPM). If the importance found then compute the value of E-learning factors like No. of Problems (NOP), Hierarchical Weight of Problem (HWP), Student characteristics (SC) and Factors Measuring Performance (FMP). Second step is to compute complexity of learning technique and problem. In case of learning technique (LTCC) compute the value of Heuristic, Algorithmic and Mathematical nature of techniques. Whereas in learning problem complexity (LPCC) compute value of design, time and space complexity for every models and assign equivalent weights. Finally, performance index (PI) is calculated by taking into account the importance (I) and complexity (CC) of learning technique and problem. Results shows that our integrated system model M10 (4.76) has highest and model M1 (1.47) has smallest PI. Model M2 (1.95), M3 (1.78), M9 (2.05), M6 (2.33) have PI which lie between interval (1.5 – 2.5). Model M4 (3.8), M8 (3.86), M5 (3.41) and M7 (3.57) have PI values which lies between interval (3.0-4.0). Chapter 8 brings the conclusion to the thesis with some future work.

Acknowledgements

First of all, I would like to express all praises to God and Gurudev on the successful completion of this research work and thesis.

Many people's support and cooperation made the present work completed. I would like to express my respect, deep sense of gratitude and indebtedness of my supervisor, Prof. Babita Pandey for her guidance, encouragement and support in every stage of my research work. I sincerely appreciate the best of opportunities Prof. Pandey provided me and credit her belief in my capability as an inspiration for achievement of my academic career. Without her insightful suggestions, fruitful criticism and useful discussions I could not complete this research.

I am indebted to Dr. Rajeev Sobti, Prof. Amandeep Nagpal, Prof. Prateek Agrawal, Dr. Devendra Pandey, Prof. R. B Mishra, Dr. Sami Radaei for valuable suggestions, friendly support and encouragement rendered by all of them. Thanks also go to CSE department and DRD members for their valuable suggestions, discussions and feedback. Further thanks to all laboratory staff and office staff of the department for their support, facilitation and encouragement during this research period.

My memory of studies at Lovely Professional University can never be complete without mentioning my fellow research scholars. Special thanks to Mr. Arun Malik, Mr. Aman Singh, Ms. Divya, Ms. Raj Grewal, Ms. Sarneet and other research scholars of Computer Science and Engineering department.

I convey my thanks to my researcher friends: Ms. Monika Rani, Dr. Vijay Semwal, Ms. Meenal Sharma, Mr. Narendra Bagde and Ms. Gitika for their kind help, good wishes, inspiration and encouragement during the time of my research to complete this work.

I must mention my family members without whom love, nurturing and support I could have never accomplished all these. I am thankful to my father, mother, wife, brother and close relatives for their support during my academic progression.

(Aditya Khamparia)

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Abbreviations

CBR	Case Based Reasoning
ANN	Artificial Neural Network
DM	Data Mining
HMM	Hidden Markov Model
SPN	Stochastic Petri Nets
AOSPN	Aspect Oriented Stochastic Petri Nets
LPG	Learning Path Generation
OR	Object Recommendation
POC	Personalization of Content
CLP	Context Learning Problem (CLP)
IR	Information Retrieval
DOC	Domain Ontology Construction
CLS	Classification of Learning Styles
RDF	Resource Description Format
SY	Syntax
LG	Logical
AP	Application
LPM	Learning Problem Measurement
LPI	Learning Problem Importance
LTCC	Learning Technique Complexity
LPCC	Learning Problem Complexity
PI	Performance Index
ELP	E-learning Problems

Chapter 1

Introduction

1.1 Introduction

Intelligent computing methods in E-learning deploy the traits of human being such as reasoning, learning, adaptation, self-organizing and self-regulation in solving educational problems of complex nature. E-learning is concerned with the study and practice of latest educational based technologies to support learning which transfers knowledge to learners and improve performance by utilizing suitable resources and processes. It is efficient as it allows learners to learn anytime and anywhere through its applications and process including web-based learning, classroom video learning, virtual learning and digital video collaborations. The Educational technologies have shifted the education from conventional classroom teaching to learners centered or dynamic learning, which provides more and effective guidance to learners to choose and learn the course material according to their needs and preferences. Due to differences in nature of learners such as skills, interest, background details and ability, there is a need to deliver suitable course material to them as per their demand, features and interest.

Adaptive E-learning system is a way to deliver the most suitable learning material to individual learners according to their needs and preferences. Most of the researchers have developed an adaptive system for teaching programming courses in computer science but they ignored to measure the performance of students at various levels in terms of delivering the course content syntactically, logically and application oriented based programs. An adaptive e-learning system based on inference engine which deployed Case-Based Reasoning (CBR) to deliver suitable learning material to learner according to their needs and preference of teaching any suitable programming construct in field of computer science. The reason for opting CBR is due to its easy knowledge acquisition, inferential adequacy and efficiency, learning new things based on past learner experiences etc.

The stated work is published in: Khamparia, A. and Pandey, B. (2015) 'Knowledge and intelligent computing methods in e-learning', Int. J. Technology Enhanced Learning, Vol. 7, No. 3, pp.221–242.

Further, Artificial Neural Network (ANN) is used to formulate the relationship between different student characteristics and their individual learning performance. Finally, data mining technique is used for classification of student features.

Adaptive learning enables online delivery of dynamic content to individual based on different level of knowledge basics, preferences, styles, motivations, course interest and acquired learning skills (Wang et al, 2011; Norwawi et al, 2009). Variety of researchers worked on content adaptation and delivery of precise content and concluded that learning capability of individual learner was not dependent only on their learning characteristics. Variety of other factors played an important role in improving significant growth of learning capability, these factors are Psychological (P) and Environmental (E) factors which enhance overall grooming of learner (Baker, 2008; Ainley et al, 2009; Hanrahan, 1998).

There are mainly two types of important factors which we have considered in this study: positive and negative. Thus, in stated work we have presented Hidden Markov Model (HMM) to predict the grade of learner on basis of their Psychological and Environmental factors and it also provide information regarding amount of complimentary factors to be provided in lieu of negative factors to improve performance. The concern behind choosing HMM is that it only considers prior probabilities (uses generative approach) unlike Artificial Neural Network (ANN), Support Vector Machine (SVM) which strictly dependent on posterior governed probability distribution (discriminative approach)

In continuation to our work for providing security in e-learning systems, varieties of threats have been classified and categorized into various categories (STRIDE) such as repudiation, denial of service, spoofing identification, data tampering and disclosure of information and providing privilege for accessing information (Howard, 2003). Variety of new modeling phases of threats framework has been introduced which fitted with stochastic and aspects petri nets. It offers varieties of applications and benefits like it is easier to run and understand application for distinct team members in effective manner, identification of faults in existing system, fault designs which are complex in nature could be identified easily which were very difficult earlier to fetch and retrieve information from existing deployed systems.

In proposed research varieties of system enabled modules are modeled using stochastic petri nets whereas different threat attenuations and mitigations are compiled using aspect oriented stochastic petri nets (AOSPN). The soundness, completeness and correctness of the aspect oriented and a normal stochastic petri nets has been measured by proposed threat driven modeling framework (Dehlinger and Nalin, 2006). Variety of new threat modeling phase was introduced in proposed work as assessment of risk, attenuation correction assessment, mitigation and disintegration correction assessment.

The performance of e-learning system for all other methods in comparison with other researcher's method has been shown. Variety of parameters we have considered to evaluate the performance of system such as prediction accuracy, satisfaction degree, concept relation degree, pre and post-test analysis and learning style standards. At last the salient features of our achievements with a scope of further work have been described.

1.2 Literature Review

Varieties of heterogeneous intelligent computing methods and related works have been performed in this section we have used in adaptive e-learning based system. We have reviewed from the following perspectives: Intelligent computing techniques in E-learning, Semantic web and Ontology on E-learning based Services, Use of Hidden Markov Model in E-learning and Security in E-learning system using petri nets.

1.2.1 Intelligent computing techniques in E-learning

In this section, we have discussed about various intelligent computing techniques (ICM) like data mining, case-based reasoning, artificial neural networks, Bayesian networks, evolutionary algorithms, fuzzy logics, rule based reasoning etc. that have been utilized in adaptive e-learning systems for various purposes such as: for detecting learning style of learner (Castro et al. 2007; Lo and Shu 2005), storing and optimally accessing the cases stored in e-learning case base (Romero et al. 2013, Kujala et al. 2010), personalization of learning objects with proper sequencing of content (Baylari and Montazer, 2009) and extracting the learning knowledge using association rule mining techniques (Chen et al. 2007b). Many researchers have been engaged in their works with usage of applications of adaptive e-learning system or e-learning problems using different intelligent computing methods.

Table 1.1 shows a comparison of the salient features of different ICMs in E-learning. This table shows the intelligent computing methods deployed approaches to handle various e-learning problems such as: Generation of Suitable Learning Path, Recommendation of Object, Content Personalization, Information Retrieval, Context based learning, Construction of Ontology for domain and Learning Styles Classification.

The learning path generation mainly emphasis on delivery of learning content or materials to the learners based on specific learning sequence and provides suitable content based on advice of system (Helic et al., 2005, Wang et al, 2007). Content personalization mainly depends on granularity of content representation and distribution for specific subjects adopted by specific learners. The classification of learning style is performed on the basis of learner's skill, mental level, interest preference, background level knowledge and important preferences (Li and Park, 2007). Context learning problem focuses on delivering and providing content for different courses to different learners at specified time interval. Retrieval of specific course content from collection of courseware on learner's request is maintained by Information retrieval (Chang, 2002). Ontology construction specifies the delivery of suitable content to learner on basis of hypertext-oriented structures.

(El-Khouly et al., 2000) provides an internet or html enabled expert system for teaching computer programming languages. They have offered flexibility to students in choosing their own programming language of interest based on their learning style and asked them to share their experiences after learning the same. The proposed system consists of three agents representing a client-server paradigm, tutoring agent as server, personal assisted agent for teachers and personal assisted agent for student as client. Due to this feature various student group queries can be handled by individual instructor agent on the basis of student needs.

(Zaiane, 2002) proposed a software-based recommender system which uses agent to provide useful guidance and suggestions for performing well with usage of online learning content. These contents helped learner to access the material fast and with limited consumption of resources. The rule mining technique on basis of associated content applied in proposed system to identify the relationship between actions and resource identifiers. They filtered out the association rules to satisfy the requirements of minimum support for learning system. They have also assigned some weightage to the rules that have uniform resource identifiers and frequently occurred URLs.

(Ting et al., 2003) have used the two layers of Feed-Forward Back-propagation algorithm to classify the question in e-learning system into three difficulty levels: hard, medium and easy. The questions have five characteristics use to identify the difficulty level: query text relevant, mean term frequency, length of question and answer, term frequency distribution and distribution of question and answer in the text.

(Romero et al., 2003) applied the prediction rule to AHA system. These prediction rules are used to discover the important relationships among usage data in the system. These data are learners usage information obtained from web based adaptive course; the teacher use these rules to obtain the trouble spots in the course in order to improve the course by making some changes in the course. These rules are used to improve the performance of learning course by applying prediction rules to learner's profiles, knowledge levels, time, score and learning material visited by learner.

(Minaei et al., 2004) have extracted useful data using data mining methods from LON-CAPA system, which involves three variety of complex data sets as informational online learning assets, information about users, and activity log data base which stores learner's homework and quiz assignments. The authors have used classifiers and integrated them with genetic algorithm in order to improve the performance. The aim of their study is to identify the grades of learners on the basis of their characteristics (total number of correct answer, correct answers at first attempt, number of success greater than 10 tries), which are expected from the homework data. The author used data mining tools to help instructors and course coordinators to design better online learning materials.

The Personalized E-learning system based on Item Response Theory (PEL-IRT) has been developed by (Chen et al., 2005). The IRT is used in education measurement to choose the better products for examining the learner on the basis of their ability and features. This prototype provides the materials as per course subject material accessed by learners, their response and the difficulty level of the course materials. PEL-IRT uses personalized agent who contains two agents feedback and recommendation agent to compute the ability of learners and to propose suitable and best course material to learners. One of the drawbacks of this system is that initially the difficulty levels of the course materials are assigned from the expert and it needs time to adjust them according to the learner's ability.

(Romero et al., 2005) described the usage of information retrieval methods in e-learning system for giving suitable feedback to courseware authors. The rules generated are known as prediction rules for improvement of course repositories called Adaptive system for internet enabled education system. The authors have used evolutionary algorithms as rule discovery methods, Genetic Programming Embedded Grammar with multi objective optimization methods. They have developed EPRules tool also known as Prediction rules for simplification of information retrieval process for data usage in internet-based education systems.

(Lee, 2005) developed a model which is suitable in e-learning environment in which diagnostic; composition and predictive roles were mentioned. Both diagnostic and predictive modeling is applied to issue of credit assignment and scalability. In context of hypermedia adaptive learning system composition modeling is used in intelligent tutoring system.

(Kristofic et al., 2005) have presented usage of data mining techniques through which behaviour of student can be determined via rigorous learning techniques and by utilizing their knowledge can deliver the next reading material content to them which they should next opt for study. They have described a knowledge-based method for recommendation of learning material and have presented design and structure of internet based system which can be used to improve adaptation.

(Chengling et al., 2006) represented the course model in directed graphs, knowledge level is specified by node and the knowledge learned by former node is acting as necessary detail for later node to make connection among them. The knowledge unit includes the course materials, concepts, definition, example and exercise. These relationships like precedence, increased and parallel can be worked for different knowledge levels.

(Encheva and Tumin., 2006) have used the association rules to find the correlation between student's knowledge and their ability to solve algebra related problems from preliminary test assigned to the students. Different student's attributes have been extracted from the preliminary test such as interest, background knowledge in algebra, experience on polynomials and matrices.

(Garro et al., 2006) have proposed a Multi agent system for e-learning and skill management which can perform various tasks: 1) to support the chief learning officer to define the roles and required knowledge level, 2) to manage the skill map, 3) evaluate human resources competence gaps, 4) create personalized learning paths according to feedbacks from learners, 5) assist chief learning officer to select most appropriate employee for a given role, 6) an agent which helps in managing the personalized learning content to build defined learning paths on basis of generated sequence, 7) an agent that captures information of all registered profile users.

(Huang et al., 2007) developed PLS-ML (Mastery Learning oriented E-learning System) which uses GA and CBR to construct the personalized learning path. This system is developed in JSP web-based interface which computes fitness function and constructs the individual learning path. During the learning process, the system assigns first unit to the learner to learn, then first assignment id given to the learner, if the learner gets a good command level in that module then he can carry out the same extension materials. If the result is less than expected level than most suitable personalized path being provided having sequence based on genetic algorithm. Each time system stores the results of the assessments and suggested curriculum sequencing paths in case-based reasoning to provide an overall result to each learner.

(Yang et al., 2008) proposed Multi -dimensional criteria system which considers Felder learning style and cognitive traits for identification of learning characteristics. Different learning profiles and characteristics were adopted in web enabled learning system for generation of personalized learning path to regulate growth of individual students learning.

(De-Marcos and Martinez., 2008) proposed a fitness evaluation function by taking a population size of 20 particles for automatic sequencing of learning objects. They aimed to minimize fitness function by giving permutation operations on randomized input sequences which will improve the velocity of generated swarm particle.

(Heh et al., 2008) have developed a full loop learning system to provide appropriate learning path to the learners. This system has four stages, analysis, feedback and corrections. In first stage, learning contents are analyzed so that material can be used for knowledge preferencing aids. The purpose of the learning diagnosis stage is to present the relationship between the concept and topics, introduce the hierarchical relationships among concepts, assign the misconception threshold for each concept, and identify the misconception. The purpose of third and fourth stage is to find appropriate teaching materials for individual learners by finding the similarity between teaching materials and learners.

(Liang et al., 2008) have proposed a framework of agent adaptive e-learning system. The authors have included all educational functions in any personalized e-learning system and implemented using intelligent agents. This system provides personalized web-based tutoring through diagnosis varieties of agents used for course selections and assignments. Learners information get stored in learner profile database to estimate the learner's ability and select suitable difficulty levels courseware for learners, to conduct personalized sequencing for learners and to provide online help to learners using agent which gives solution to queries given by the learners with appropriate answers provided by instructors.

(Schiaffino et al., 2008) have presented eTeacher, which guides e-learning students and provides personalized assistance to them with the help of an inference agents driven system. It considers and adopt different characteristics of students and considers motivational features to construct students profile and managerial activities. Students performance could be judged on basis of exercises completion, results analysis and topic to be studied using different learning styles. The action or student behaviour in e-learning system is responsible for automatic identification of learning styles achieved through Bayesian networks. E-Teacher module provides assistance to learner by suggesting different personalized course which helps them during understanding of learning process.

(Kerly et al., 2008) offered a learner model which heavily relies on machine-based computation, NLP and data base management technologies. After combining such advanced technologies, they have built an intelligent learning system which provides opportunity to learners to compare their belief-based system with other systems capability. In their work a personalized multi agent system have been developed which uses principle of item response theory for computation of learner skills and abilities of learning. Variety of agents are indulged for diagnosing the problem of learner by working as an instructor and recommend appropriate materials to them on the basis of their needs and preferences.

The prototype Dynamic Learning Path Advisor (DYLPA) proposed by (Wong and Looi., 2009) to recommend a learning path to the learners is based on perspective rules. The learning path for a learner is generated based on the learner's performance logs in the system. The system selects specific numbers of previous learners who have similar profiles to the new learner, then the performance of learners is analyzed using Swarm intelligent technique to induce a path for new learner.

(Wang and Liao., 2009) presented an optimized system for learning sequence detection and monitoring. For learning content, most adaptive learning sequences has been discovered using decision tree algorithm on basis of student profile having student characteristics as gender, personality, cognitive style, learning style and student grades from previous semester. Their approach maximizes the learning outcome of students by providing an optimal dynamic learning sequence to them instead of providing fixed or traditional sequence. The given system defines different level of material to be delivered on basis of vocabulary, grammar with different characteristics combinations.

(Bhaskar et al., 2010) proposed an adaptive learning scheme to accommodate various context of learner in e-learning environment. This model able to classify the different learning styles based on Felder Silverman, Likert scaling etc. Their Genetic based model uses chromosome strings which consists of 3 different genes, higher crossover and reproduction supported by model. Their goal was to maximize the fitness function criteria which are based on learning one object with respect to another object.

(Ghauth and Abdullah., 2010) proposed an ANN based recommendation system that optimizes the learning path which is generated and improve the score computed by learner based on keyword matching. They have preferred vector performance indicator in their model which enhanced the efficacy and achieve high precision with accurate efficiency. Automatic keyword has been assigned to words present so that similarity between documents can be found or retrieved easily.

(Hsieh and Wang., 2010) proposed an online e-learning to generate a learning path based on the learner's preference and requirement and to recommend the suitable learning object. This system collects the documents and learning resources from the web and selects the learning unit using data mining method based on Apriori algorithm. Learning units are processed using adaptive term frequency inverse document frequency and formal concept analysis algorithms to extract the significant keywords in learning unit. After that system generates the hierarchy relation between concepts in the learning units and used FCA to generate the suitable learning path.

(Wang and Liao., 2011) presented an Adaptive Learning in Teaching English as Second Language system (AL-TESL) for e-learning. This system provides learning materials for the learners based on their gender, personality and anxiety level. Back-propagation algorithm is used for supervised cluster of learning characteristics and learning performance. The system identifies the relation between learner's characteristics and learning performance to obtain different levels of learning performance, then determining the learning content of different learning performance for different combination of learner characteristics.

(Guo et al., 2011) proposed a recommendation system driven by ontology and Bayesian analysis. This system work on basis of personalization of context and delivers individual learning material to student on requirement of their learning style. The performance, loyalty and efficacy of learning get improved by incorporating the cognitive ability of individual learners. The domain ontology was preferred for constructing the knowledge base and improves the probability distribution of different learning materials presented to learners.

(Romeo et al., 2011) presented a fuzzy ontology-based e-learning system or recommender system which decreases the learning time cost to retrieve the user profile as per their requirement and needs. Due to this system clustering, categorization of learning content and deployment got easier and knowledge inferencing improved a lot.

(Anari and Anari, 2012) proposed a MLP network model on basis of forward and backward reasoning. They have used Markov method which predicts behaviour of new learner on basis of their past experiences to achieve high accuracy rate.

(Seters et al., 2012) proposed an adaptive e-learning system by determining features of student units by gathering information on their previous knowledge, motivational skills, interest and abilities. Learning path followed by students who studied molecular biology course is based on learning strategies. Students who belong to post graduate stream follow different learning path and strategies with consideration of intrinsic motivation when using adaptive e-learning material.

(Parthiban and Sekar., 2013) used adaptive learning rules to match relationship between learner and learning objects. They have generated rules to identify which learning object is to be recommended next. It provides strong searching capability, local heuristic search and ability to converge information quickly as soon as object gets recommended.

(Lin et al., 2013) developed a PCLS System which uses data mining techniques i.e. decision tree for providing optimized learning path to improve the performance creativity. They have provided a questionnaire to students to check their creativity score based on their gaming skills. After successful implementation of PCLS, when learning path is employed it suggested that mining of data will be useful for delivering and considering adaptive learning creativity and enhanced their motivation and learning effects.

(Al-Radaei S., and Mishra R., 2013) presented a heuristic method for learning path classification in E-learning system. Two assumptions have been used to construct the learning path sequencing. First assumption is that each courseware has previous content available with them; second assumption is that each courseware has some important keywords; meaningful values are assigned to those keywords on the basis of their occurrence with respect to the coursework as well as the coursework. Learning path sequencing has random mode which offers ability to choose course ware by the learner. Semantic value obtained for selected course ware is maintained the relationship between different modules of courses.

(Chakraborty et al., 2014) proposed an intelligent fuzzy spell-based evaluator which checks the spelling of learning content before presented to learners. They adopted a two-fold strategy which evaluate the response of learner in term of words, letter sequences and predict the positional errors if occur any while formulating sentence. These sentences are checked by efficient fuzzy decision making function and generates an accurate answer.

(Pandey et al., 2014) developed an adaptive C programming-based e-learning system which comprised of several distinct student characteristics. CBR is preferred to enhance the student's performance. In C programming test questionnaire has been given to student which comprised of programs type SY, LG and AP categorized at various granules on basis of feedbacks received from students. The result optimization of experimental group is compared with control group and achieved better performance of those who relied more on case-based oriented approach.

(Kardan et al., 2015) presented content analysis of different adaptive e-learning systems suitable for e-learning environments. They presented statistical analysis on adaptive technologies used by different researchers from 1990 to 2010. They have discussed work on basis of adaptive intelligent computing techniques used and various application field driven systems.

(Fatahi et al., 2016) discussed various human cognitive behaviour and learning style which had impact on overall grooming of individual learner in e-learning environment. They had reviewed various personality (five factor model, Briggs indicator) and learning style models (Felder Silverman) and abstract common feature properties as simplicity and comprehensive power which gained more attention among e-learning researchers community of virtual world.

(Troung., 2016) suggested variety of adaptive e-learning systems by integrating different learning styles, predictor classifications, learning applications and recommendations. They have provided future research directions in field of e-learning environment by integrating statistical techniques with hybrid and ensemble mode of learning. The integration and usage of adaptive e-learning systems also included in multimedia and game driven systems.

(Zare et al., 2016) provided multi criteria driven decision-based approach for classification of e-learning systems. These problems deal with different decision driven problems as classification, ranking and provide robust solution in solving different e-learning related problems. They involved choice, intelligence, design and implementation phases for solving multi criteria decision making approaches to solve multiple e-learning problems.

(Rani et al., 2016) created an ontological knowledge profile which learner has to follow and knowledge associated to it. The management of learner profile could be done with help of VARK driven learning style. The intended learning style allows to deliver learning content as per suitability and need of learner. The learners path would be aligned with help of ontology which manages their profile and provide recommendations.

(Latha et al., 2017) presented an evolutionary approach for delivery of learning content to different learners. The proposed approach personalized the process of learning by tuning compatibility level of learning style with suitable learning objects, complexity level gets tuned with help of knowledge and interactive level using genetic algorithm. Learners score has been improved by forcing compatibility level into the system which reduces execution time and improves fitness value.

(Yilmaz R., 2017) proposed model for improving satisfaction and motivation level of learning students in flipped classroom environment. He investigated whether individual learner is ready to deal with structured equation modeling which verifies the readiness of students on basis of path followed by them.

(Srivastava B. and Haider T., 2017) designed a personalized model or framework for students who suffered from dyslexia. They designed alphabets as specific learning objects and built a platform which used or tried to solve e-learning related problems which students were facing. The feasibility of study could be validated as they have tested their framework in various school premises.

In Table 1.1 first column denotes the author name; second column describes the ICM deployed; third column represents the E-learning problems and approaches to handle them; column fourth represents the specific features and Implementation has been represented by fifth column.

Table 1.1 Intelligent computing techniques in e-learning

Authors Contribution	Intelligent Computing Method Used	Problem Handling Approaches; E-learning problem	Distinct Features	Implementation
El-Khouly, Far and Koono (2000)	Multi Agent Systems	Generation of learning style with usage of dialogs and modify required structure; CLS	Enables interaction among student, teacher and teaching agent	JADE
Zaiane (2002)	Association Rules	Needed Resource identification and navigation with the help of Recombination systems; OR	Learning accuracy improved via usage of effective learning contents	Not Specified
Silveira and Vicari (2002)	Multi-agent (ELTOR	Automatic enabling of learning mode through e-	JADE driven system with remote, student, pedagogy and	Not Specified

	Tutor)	learning environment interaction; LPG	information communicator agent.	
Ting et al. (2003)	Feed forward back propagation algorithm	Utilizing adaptive features for question classification into different classes; IR	Fetching and retrieving textual information is easier at different granular levels	Not Specified
Romero et al. (2003)	Predication Rules	Trouble spot identification is very difficult in e-learning environment; IR; OR	Good precision and high efficiency achieved	Java environment (J2EE)
Minaei et al. (2004)	Genetic algorithm is adopted where learner string consists of courseware sequence, initial population length is fixed, effective reproduction, mutation of single flip, crossover pointed is adopted, objective function depends on answer classification and stopping criteria is achieved until path not completed	If answer is correct then marks will be awarded for problem correctness; CLS	Overall overhead reduced	LON–CAPA System
Chen et al., (2005)	Genetic Algorithm: String sequence consist of different course types, population size is of 50, multi uniform crossover, multi flip mutation: 0.1, objective function depends on	For different content of coursework suitable learning objects are recommended on basis of path sequencing	The courseware continuity is very difficult to maintain as number of parameters being increased in objective	C platform and clementine tool

	time spend on learning and time required for actual learning sequence, stopping criteria is set to 200.	followed by them: LPG; OR	function.	
Romero et al., (2005)	Grammar driven genetic programming multi-objective optimization	Successive feedback given to course content designers; LPG	System performance improved by assigning skills, interest and preference to learner which optimize best learning path obtained for next coming sequences	Java
Kristofic and Beilikova (2005)	Associated Data mining with pattern and traversal structures	Student behavioral knowledge explored due to adaptability of course material; CLP	Reduction of error and information retrieval is easier to perform	Not specified
Chengling and Liyong (2006)	Directed graph-based Bayesian Model	Learner request created an appropriate path generated for learner which determines the handling of response achieved then learner proceeds; LPG	Higher satisfiability, expansibility, and interoperability achieved	Not specified
Garro et al., (2006)	Profiler agent System	Personalized Learning path being provided to	Learning path is achieved by involvement of various agents	NA

		learners; LPG	like content delivery management, learning path agent and officers agent.	
Encheva and Tumin (2006)	Association rules	Correlation needs to be preserved by gaining knowledge of students and solve algebra related query finding problems; CLS	Searching of individual questions through obtained solution is correlated to gain better results	Java
Huang et al. (2007)	Promising learning path is constructed by utilizing genetic algorithm and case-based reasoning	It considers pre-post methodology for data validation and does not consider learners interest, goals, mental knowledge level, skills, preferences and motivations; LPG	High level successive curriculum with different difficulty levels to be considered for generation of personalized optimal learning path	Java
Heh et al. (2008)	Heuristic Method	Formulation of concept; CLP	To establish hierarchical relationship among concepts and knowledge map matrix representation is used.	Not specified
De-Marcos and Martinez (2008)	Uses 20 particles, randomized by sequence of inputs, objective and minimized fitness function value	Permutations enables learning sequencing; LPG	Velocity of particle improves performance	Not Specified

Yang et al. (2008)	Personalization based adaptive system	Adaptive personalized system by considering different student features which involves Felder and their related cognitive traits OR; CLS	Updation of profiles to produce learning path for students	Not Specified
Kerly et al. (2008)	Tutoring based multi-agent system	Improve overall development and define procedure to conduct self-assessment in learning; OR	Different agent types like avatars, pedagogical. Conversational and tutorings are used.	JADE
Liang et al. (2008)	Multi-agent System	Learning path planning, Interactive system; LPG	Experts, courseware specialist and navigation agents are used to improve learning functionalities	Not specified
Wang and Liao (2009)	Decision tree Analysis	Maximize individual learning outcome of students by providing good sequencing; LPG	Student performance increased and learning cost also reduced teaching cost.	Not specified

Hsieh and Wang (2010)	Apriori Algorithm	Keywords used for document extraction and discovery done by mining to form concepts lattice represented by documents; LPG, OR	Generation of path is improved by usage of retrieval systems embedded for various contents	Formal concept Lattice
Bhaskar et al. (2010)	Chromosome strings consists of 3 gene types which has higher mutation, crossover and reproduction; objective function based on learning material content and criteria for stopping is till mutation converges.	Adoption of learning content in different contexts using genetic concepts is difficult; CLS	Various constraint satisfaction related problem being handled,	J2EE and HA System
Halachev (2010)	Artificial Neural Network Construction with vector driven performance parameter	Key indicators enhance learning performance for model efficiency and accuracy; CLS	Effective precision rate required by different neural networks to enhance academic	Java framework for score generation

			performance in Universities	
Ghauth and Abdullah (2010)	Artificial Neural Network driven recommender system	Object recommender system proposed which utilizes keywords to improve generated learning path and students score obtained through experience; OR; LPG	Document similarity is achieved by automatic assignment of keyword and improves learning performance through usage of documents	Weka and Java
Hsieh et al. (2010)	Web based system using Association rules and Apriori Algorithm	Generation of learning path using web enabled learning system which specified user's preferences and requirement and to recommend the learning object; LPG; CLS; POC	Hierarchy relation between concepts in learning unit and uses formal concept analysis to generate the suitable learning path	Data mining system
Zhang et al. (2011)	Rule based Reasoning and Artificial Neural Network	Teaching strategies are adjusted by production rules and emotions are identified, recognized and trained by usage of neural networks; IR	During learning content identification high recognition accuracy is achieved	Not specified
Wang and Liao (2011)	GA: Chromosome Strings used for	Genetic algorithm generates optimal clusters and	Experimental groups outperform	Java

	initializing population of random size; clusters are generated by objective function; cross over ranges from 0-1, 1000 steps or epoch was stopping condition	provides effective and cooperative learning; LPG	control group and achieve higher performance in communication related competencies like watching, listening etc.	
Romero et al. (2011)	Fuzzy ontology-based e-learning	Management and classification of recommendation system updates user profiling with Fuzzy logics and information handling is difficult for cost retrieval; POC	Effective precision and high accuracy rate is achieved for several learning objects	Fuzzy based MATLAB simulation network
Guo et al. (2011)	Recommender and Bayes analysis-based ontology driven	Personalized recommendation and improvement in content pedagogy is difficult in e-learning system; POC	Usage of cognitive ability improves loyalty, performance and effective teaching	JDK and protégé
Wang and Liao	Back propagation algorithm	Students features classified on different course context level;	Various levels indicate improvement in learner	Not Specified

(2011)		CLP	performance	
Anari and Anari (2012)	MLP model used to perform gradient based backward and forward phase learning	Markov model and related hidden sequence is used to determine new learner behaviour on basis of past learning experience and provides high accuracy; POC	Improvement of education system on basis of forward learning	AHA System
Seters et al. (2012)	ANN based recommender system	Adaptive e-learning system by determining features of different group of students by considering prior knowledge, motivation level and personalized data; LPG	Improve learner characteristic using adaptive e-learning material	Java
Tan et al. (2012)	GA-Ontology and domain dependent course generation for personalized content	Enhancement of learning performance on basis of different difficulty level of questions and adaptive courseware construction; POC	High efficiency enabled best course sequencing with usage of domain ontology	Protégé, Java
Parthiban and Sekar	Ant Colony Optimization (ACO)	Establishment of relationship between learner and object with usage of adaptive	Learning materials used to solve different constraint satisfaction	Not specified

(2013)		match-based rules; OR	driven problems to achieve better accuracy	
Mahmoudi and Badie (2013)	Semantics based on Rule and Frames	Query retrieval mechanism with different rules to analyze learning material for educational media; IR	Linguistic knowledge used to construct high precision rules	C environment and Altova (2009) networks
Al-Radaei S. and Mishra R., (2013)	Multi Agent System	Updation of learner profile based on Semantic value of keyword for score and path sequence calculation; OR	Usage of agent and Semantic keyword provides higher accuracy for descriptive type questions	JADE
Chakra-borty et al. (2014)	Fuzzy based Evaluator	Computation of positional error and their evaluation using fuzzy based and two fold strategy is difficult;CLS	Word occurrence and its correctness being improved with usage of accurate answers	Fuzzy based Framework
Pandey et al. (2014)	Case-based reasoning	Adaptive Programming system utilized several student features	Learning performance of student gets improved by using case oriented approach.	C based system
Prabagaran et al.	Context dependent assumption-based method	Activity and profile enabler database adopted	Ontologies in different context enable	OWL and SNAP

(2014)		to enhance learner's performance for different context problems; CLP	interoperability of semantic information for different domains	

1.2.2 Semantic Web and Ontology on E-learning based Services

Semantic web transforms web into repository of readable data which is beneficial for computer, whereas web services provide tool for automatic reuse of that data. The representation of that data could be done with the help of ontology which redefines and structure the domain knowledge in hierarchical form. Table 1.2 shows a comparison of the salient features of Semantic web technologies, Ontologies and Web services in E-learning. This table shows the intelligent computing methods deployed approaches to handle e-learning problem, specific feature and their Implementation details.

(Stojanovic et al., 2001) proposed usage of semantic web enabled tools in e-learning scenarios. They have used annotations which describes the topic created by learning material, the ways through which learning material is categorized and determine the navigational way exists among different learning materials. This approach constructs the new online content or materials by combining the previous existing learning contents. The system handled the meaning full based queries or information easily by defining the suitable learning content which best suited the program and fit as per student needs.

(Dolog et al., 2004) described the system which focuses on reading of personality of learner. This system 1) enhance the reading habits of learner by mentioning suitable examples, sequence based information, exercises in form of quizzes and puzzles which facilitates learner to arrange and categorize the questions raised by them during availability of various resource material, 2) provide the learner with references to additional sources from meaningful web content which comprised of all the visited and used resource of learning which helps to enhance their knowledge of learning by improving skills of background, interests etc. The learner submits a query to retrieve a learning resources, query is revised by encompassing the preferences of learners and the features considered for utilizing the existing resource material.

(Kotzinos et al., 2005) presented an online curriculum portal using semantic web technology. In their proposed work learning content are used to define an object, RDF and SWRL based query are used to show relationships among different learning materials which can be represented easily. Such kind of emerging techniques will define learning path based on personalized theory which comprised of learning object sequences that student can follow while choosing subject topic of their own interest either as individual or in group.

(Mencke et al., 2007) used didactic knowledge to enhance e-learning based on ontology representation. Varieties of levels have been discussed by authors in which first level contains the general ontology of didactic strategy which involves multiple learning paths. In next level teacher and student relationships are defined hierarchically. Last level contains didactic models which describes each adaptive didactic individually. These ontologies provide a shared vocabulary for teachers, designer and experts.

(Glandun & Rogushina, 2007) have proposed a model of multi-agent ontology-based e-learning system. This system includes student agent and course tutor's agent which help persons to search for the information required for them. The ontology is used to describe the course materials and to represent the student belief about course domain. The student builds required learning information ontology and sends it to the system, then information agent compares this ontology with the ontology from the tutor, then the result is sent to both student and tutor. The tutor agent provides the required information if there is no need for instruction from the tutor. The student receives a notification in case of a mistake of building ontology for the same type of different courseware.

(Su et al., 2007) have suggested that e-learning system can be assembled into two sets of services: 1) high level functionalities which are education focused such as awarding marks to students, their assessment course management and organizing content for dynamic web services. In this work, the author have developed e-learning framework which comprised of distinguished layers: 1) presentation layer provides an entrance way for accessing web based services, 2) E-learning services layer which provides the e-learning functionality assessment, grading, marking, course management, meta data, enrollment and assembling of e-services, 3) general procedure which provide the services that are not dependent on any e-learning functionality such as authorization services, search services and annotation services.

(Klusch and Kapahnke., 2007) proposed logic and text matching-based hybrid selection of process in Semantic Web driven environment. During selection of service they have not adopted the cognitive parameters and related queries used for selection of semantic web driven services. The index generated by model is relatively worked on discrete governed mechanism. They used the indexing for matching the logic from one text with other text and inserts the qualitative information at suitable places obtained from SAWSDL approach.

(Millard et al., 2008) presented an e-learning system based on semantic web services. Different ontologies on subjects, questions and related syllabus were used to represent the learning materials. The syllabus ontology has represented the structure of the concept and relations involved in describing the course. The syllabus and question ontology shared the relation from subject ontology. Various web services used for searching the question in which basic search service uses simple attributes from question ontology and final search used the annotated data in three ontologies of the system to demonstrate the knowledge base.

(Kumar and Mishra, 2008) have proposed rating of different semantic web services based on cognitive parameters but they have not adopted Quality of service driven rating for selecting appropriate service for any model. They considered the impact of cognitive parameters for different level of web service selection in different context using multi-agent's system. It eases concept of interoperability and service selection but not focused on non-functional attributes. Unique selection models based on persuasion, trust and reputation based QoS parameters have been considered by an author in their work.

(Zhao and Zhang, 2009) proposed an e-learning system which adopted ontology and knowledge management related technologies. The ontology library where learning materials stored provides a vocabulary sharing of the concepts of the learning material in order to save time and cost for teachers and students. It helps students and teacher to share teaching knowledge, searching knowledge and documents from knowledge base and provide feedback to students.

(Zhen, 2009) presented virtual e-learning system which contains three components: learning administrator, learning supportive machine and two learning subsystems provide different learning content and services. The web service verifies the prerequisite course information which is used to check study the previous material of learners and to verify that learner has accomplished the prerequisite of the course he wishes to register to. The service engine is responsible for aggregating content from different sources on the basis of required information for binding the features found in UDDI. This system is built on the basis of HTML and JSP and messages among the agents are based on Java Message Server.

(Kumar and Kumar, 2009) proposed Quality of Service and cognitive parameter-based hybrid selection model which selects required service through normalized procedure and affects the image of service ISPs based on the service quality offered. Their approach focused on QoS strategies which improves selection accuracy and service delivery speed with the help of feedback mechanism. They considered rating to individual learner or user but no specific input being considered on scientific search strategy.

(Deborah et al., 2012) proposed deontic logic-based ontology alignment system using SWRL. Deontic rules are used for identification of verbs and determiners which occurs in text documents and after ontology gets aligned it improves the performance and accuracy while evaluating the ontology knowledge base. By using this method, the text prediction gets easier in ontology system.

In Table 1.2 first column denotes the author name; second column describes the ICM deployed; third column represents the E-learning problems and approaches to handle them; column fourth represents the specific features and Implementation represented the fifth column.

Table 1.2 Semantic web technologies, Ontologies and Web Service

Author name	ICM deployed and their parameters	Approach to handle problem; E-learning problem	Specific feature	Implementation
Stojanovic (2001)	Domain ontology driven personalized e-learning	Context based learning materials used in e-learning system; CLP	RDF used for learning material description	SNAP framework
Dolog et al., (2004)	Adaptive context driven ontology	Global and local context used for delivering personalized content to learner; POC	Hypertext Used for context identification of learner	Not Specified
Gascuen et al. (2006)	Domain ontology e-learning	Domain ontology used for prediction using silver learning style; CLS	Domain constructions used for web mining encapsulation	J2SE and Tomcat Apache
Mencke and Dumke (2007)	Ontology Driven	Enhance e-learning based on ontology construction; DOC	Three level structure used to represent learning relationships	Clementine and Java featured
Klusch and Kapahnke (2007)	Logic and Text based Matching	Service selection approaches without cognitive parameters	Good and efficient retrieval system which improves	SAWSDL system

		consideration; IR	the overall performance	
Kotzinos et al. (2008)	Ontology Driven	Provide learning content with appropriate navigation view and queries; CLP	RDF and query used to generate learning path	SWRL and Java
Millard et al. (2008)	Ontology driven	Most appropriate content being searched by learner; CLP	Question, subject and syllabus ontology used	JSP with protégé aid
Kumar and Mishra (2008)	Cognitive driven multi-agent systems	Cognitive parameter used but not considered QoS for service selection; LPG	Eases concept of interoperability and service selection but not focused on non-functional attributes	Java
Chao and	Semantic	Semantic enable searching documents	Learning materials are	Not specified

Chang (2009)	Ontology	from knowledge base learning; CLS	stored in ontology	
Kumar and Kumar (2009)	QoS parameter-based hybrid selection model	Learner questions classified on based on some adaptive features or cognitive parameters which improves selection accuracy and speed of service; IR	Learning ontologies are used to keep tendency but no input on scientific search strategy	Not specified
Maryam et al. (2013)	ITR based context driven ontology	Adaptive content sequencing for learners based on learning and representing style to calculate learners ability their knowledge progress; LPG	Learners model Used instruction profile to identify knowledge progress of learners.	ITR recommender system in Java
Awan et al. (2013)	Social personalized adaptive learning ontology	Identify learners characterization using simple questions; LPG	Likert scale used for construction of ontology	Weka and Java

1.2.3 Use of Hidden Markov Model in E-learning

In this section, we have reviewed about Hidden Markov Model (HMM) which is a special case of dynamic bayesian networks used to model probabilistic sequence in a network and used to solve problems in area of personalized and adaptive e-learning systems. In E-learning system the major goal of HMM is to infer probabilities for any given state i.e. to personalize the web content according to browsing and behavioral experience of user.

Many researchers have been engaged in their works with usage of applications of adaptive e-learning system or e-learning problems using Hidden Markov Model. Table 1.3 shows the HMM deployed approaches to handle various e-learning problems such as: LPG, OR, POC, CLP, IR, DOC and CLS.

(Jeong et al., 2007) determined impact of cognitive and motivational behaviour on learning performance of individual defined in different learning environment. HMM determines individual frequency count and learning behaviour of individual without examining coherence of behaviors exist among pattern of different sizes. Their approach takes into account different random samples of student's behavior apart from focusing on specific modified behavior and observations determined at that instant of time.

(Su et al., 2007) have suggested that e-learning system can be assembled into two sets of services: 1) the high-level functionalities which are education specific such as assessment, grading, marking, course management and reporting web services; 2) common services provide a low-level functionality which is application services and uses HMM modeling. They have proposed e-learning framework which provides e-learning functionality assessment, grading, marking, course management, meta-data and registration facility. They also managed common services which provide the services that are not dependent on any e-learning functionality such as authorization services, search and annotation services. The resource layer provides the underlying infrastructures.

(Severac et al., 2012) developed HMM evaluation system which could be useful for students and instructors. Most of the students pointed that this system is easy to handle and effective in usage in the introduction or beginning part of it. Whereas more than 60% of the instructors had positive intent about the recommender system. The survey conducted for satisfaction analysis showed that most of the group become agree or disagree with respect to the usability and easiness of the system and create an intelligent ITS system.

(Deeb et al., 2014) presented a distinguished method for designing of an e-learning system with delivery of content i.e. adaptive based. Their approach identified an exclusive learning trait and imparts the quality learning content to students. They have proposed a research model on the basis of students clustering using K means algorithm delivery of learning material content is characterized mainly for individual students based on their skills, background knowledge, and attitudes etc. using Hidden Markov Model. Their proposed adaptive algorithm effectively managed the clustering of student's data based on their visual, learning, audio and kinesthetic learning style and identify the different online learning which determines the future e-learning module for learners. This algorithm is effectively utilized in cross platforms e-learning based environment where optimal learning material can be delivered in real time.

In Table 1.3 first column denotes the author name; second column describes the ICM deployed; third column represents the E-learning problems and approaches to handle them; column fourth represents the specific features and Implementation has been represented by fifth column.

Table 1.3 Comparative view of Hidden Markov Model used in E-learning Systems

Author	ICM deployed	Handling of E-learning problem	Specific features	Implementation /Applications
Fok et al. (2005)	Hidden Markov Model with content based patterns	Initiate user profiles to predict and anticipate their needs through content navigations; LPG and CLP	Adaptive user interface design, Personalized tool in learning system	Multimedia e-learning systems
Jeong et al. (2007)	Hidden markov model with meta cognitive behaviour	To extract the student interaction patterns from system log files	Entire student behaviour get captured rather than focusing on individual	Java

		by observing student behaviors, IR	behaviors	
Su et al. (2007)	HMM modelling	Authorization and search annotation services being handled by model according to specific web services, LPG	System provides functionality assessment, grading, marking and registration facility	Smart WebCom
Severac et al. (2012)	HMM based Evaluation	Recommender system with effective usage for instructors, IR	Usability and Ease of usage with technology acceptance	ITS System
Deeb et al. (2014)	Adaptive HMM with K-means algorithm	Algorithmic delivery of learning material to learners on basis of clustering; LPG	Visual, Audio and Kinesthetic learning style adapted to deliver learning material	Web based framework
Latham et al. (2014)	Adaptive HMM system	Average score gets compared among two groups of students to check the proposed system efficiency, CLS	Efficiency of system get improved, robustness, easy to use	Web based system

1.2.4 Security in E-learning Systems using Petri Nets

In this section, we have reviewed petri nets which is an event driven tool used to model time event driven e-learning systems. On basis of formal techniques various e-learning systems are designed which provides threat modeling only in requirement phase whereas petri nets provide security in design and analysis phase of software-based e-learning systems. Petri net enabled the threat mitigations at various stages of e-learning system. Various researchers have been engaged in their works with usage of applications of adaptive e-learning system or e-learning problems using Petri nets. Table 1.4 shows the Petri net deployed approaches to handle various e-learning problems such as: LPG, OR, POC, CLP, IR, DOC and CLS.

(Mikolajczak and Joshi, 2004) proposed a pragmatic approach in which security have been incorporated into an existing non-security model. They preferred CPN development platform in which color petri nets have been used for model designing. Their information system model incorporated security features such as confidentiality, data integrity and non-repudiation using color petri nets. They have incorporated confidentiality feature in conference submission process system by maintaining the confidentiality of content of paper submitted by authors. They have used Color petri nets for development of new communication-based system with enhanced features. These security features are aided as an extra asset for existing CP model. Due to this, new security-based model of their own interest has been used which covers: confidentiality, service integrity, authentication, data integrity, and data secrecy. This model can be refined many a times to prove its worth through method of verification and validation.

(Zhang et al., 2005) introduced hyper-text based learning applications for different learning applications which involves petri nets. They proposed a high level timed base petri net approach to provide variety of adaptation for different e-learning activities. Their proposed approach interprets the browsing semantics of learning state space using hypertext learning and provides adaptive operations delivery using content, link and timing priority adaptation. Timed petri net was used to model temporal events occur in system. Such type of discrete events can be used for reading hypertext, typing words etc. which enables embedded path control information in petri nets structure which attempts to realize learning methodology.

(Diangxiang Xu, 2006) developed a threat driven based model approach to enhance or exploit the behaviour of threats which can worked as intermediator for various security breaches or design and specific application oriented features. They have preferred aspect oriented model in their approach in which security threats and functions are modeled and threat mitigations get modeled by petri net based aspects due to incremental nature of security measures. Based on results concluded more compact software design can be made which is better and cannot be threatened by threats and helps in reducing the vulnerabilities present at the design level.

(Borges et al., 2010) demonstrated the usage of petri nets in educational context in e-learning based collaborative environment. They proposed a tool called TeleMelos which supports e-learning as the professor in that system become the main element which acts as the core unit of the educational process in order to understand the behaviour of system and existing methods. They have used mediation as communication mechanism in which participants communicate verbally and modeled scenario in such a manner that user competes for competitive computational resources with the help of collaborative tools.

(Sherief et al., 2010) presented a threat driven modeling framework to determine which threats require mitigation and how to mitigate those threats. They defined software based security metrics for identification of vulnerabilities using adaptive approach which determines the quality of software product and its impact in modeling the threats. They have used Common Vulnerability Scoring System (CVSS), standardized procedure for rating the vulnerabilities present in software which was used as the basis in the metric definition and calculations.

(Omrani et al., 2011) proposed a new adaptive method for adaptive learning which considers adaptation using some viewpoints on basis of learners learning style, knowledge level and learners score. They preferred high level petri net using similarity between learning object graph. Through performance evaluation method they compared adaptive system with conventional learning systems in which the response time achieved by their system is very less compared to non-adaptive system. They also claimed that their proposed system considers individual learning features of students so that learners would not get confused while preferring learning materials of their choice.

(Amin et al., 2011) proposed a Moodle based model which involves petri nets and use smart intelligent E-learning techniques for the purpose of modularity and personalization. These systems are not that much adaptive as per the changes or amendments performed in incoming data for facilitation of Moodle parameters like static course material delivery. They have introduced a new fuzzy based petri net system called AFHOPN which adjust the behaviour dynamically and measure the rate of learning by seeing the inferential capability of intelligent E-learning based systems.

(Balogh et al. 2012) have made a learning management system which is based on petri net design and delivers the communication to student according to their needs, preferences, skills and abilities. Variety of personalized feature considered by them without any involvement of metrics which can be used for improvement of reliability, parallelism, robustness and consistency of system.

(Kamceva E.S. and Mitrevski P, 2013) proposed modeling of an educational system using formal models based on petri nets. This method helped to determine the time taken by e-student in estimating the state which he had to captured. Many techniques are used for this purpose but a petri net graph based model has been chosen by them. The exams conductance, their titles and examples are acting as place in petri net system and color token represents students or learners.

(Hammami S., and Mathkour H., 2013) developed an internet enabled system which emphasis on adaptive learning with the help of various multi agents. A new category of petri net system called object petri net have been used to build super scalar architecture to adapt the learning material and its content as per the preference available and controls the interaction, availability of service and communication among individual different agents.

In Table 1.4 first column denotes the author name; second column describes the petri nets deployed; third column represents the E-learning problems and specific features and Implementation has been represented by fourth column.

Table 1.4 Comparative view of Petri net modelling system for E-learning

Author	Methodology	Specific features / E-learning problems	Implementation/Application
Mikolajczak and Joshi (2004)	Pragmatic with Color petri nets	Confidentiality, data integrity and non-repudiation have been incorporated into non-security models; DOC	CPN Environment
Zhang et al. (2005)	Timed petri nets	Browsing semantics	Hypertext learning

		of state space operations get improved and provide link content delivery and priority adaptation; LPG	applications
Borges et al (2010)	TeleMelos petri nets system	Educational context used meditation as communication medium through which computational resources get approved with the help of collaborative tools; CLP	Educational System
Sherief et al (2010)	Petri Nets with CVSS	Threat driven modelling framework proposed with CVSS to compute the vulnerabilities; LPG	E-Security Web system
Amin et al. (2011)	Fuzzy based Petri nets	Modularity and Personalization of fuzzy petri net based system get adjusted dynamically by measuring the learning rate and inferential capability of intelligent learning systems; OR	Web based Systems
Omrani et al. (2011)	High level petri nets with object graphs	Adaptive learning using learning style, knowledge level and learners score through which preferred learning material delivered to learner; LPG	Web based system
Balogh et al (2012)	LMS based Petri nets	LMS delivers the material to student according to their needs, preferences, skills and abilities. Reliability,	Personalized Web based System/Mobile App

		robustness and consistency of system get improved; LPG	
Kamceva and Mitrevski (2013)	Formal color petri nets graph	Student spend more time in non-adaptive based system rather than adaptive. The purpose is to determine time taken by e-student in estimating the state to be captured; CLS; OR	E-student system
Hammami and Mathkour (2013)	Multi-agent based object petri nets	Super scalar architecture with interaction, availability of service and communication among agents build to provide adaptive learning; CLS	Peer to peer Web System

1.3 Motivation

Some observations have been made from the literature review given above.

- It is observed that various methods in development of E-learning have been reported in the literature.
- Most of the researcher's emphasis on considering the learners characteristics like personality, anxiety, cognitive behavior etc. but there is no work that considers the case -based system in which attribute value pair is used with lower and upper bound related to individual learner characteristics.
- Very limited numbers of works are available for personalized learning strategy.
- Learners performance is an important issue in learning strategy.
- It is also found that HMM and Petri net paradigm is an active area in E-learning.
- It can be observed that the data mining, CBR and ANN are an important technique which provides course content of distinguished features to individual learners based on their characteristic and demographic features. Artificial Neural Network enables relationship between different learning features of learners and performance achieved by them. Data

mining enables generation of different rule set of various sizes using classification algorithms where rules are further fed into case driven inference engine where cases are stored for reasoning activities.

- Variety of multifarious researchers are addressing the problem of search driven content which are generally engaged in moving profitable direction for accessing learning materials and resource available on web. There is a need to manage the learning materials in order to deliver them to the learners according to learners demand, interest, knowledge and background skills.
- Very limited numbers of works are available which try to incorporate Hidden Markov Model and Petri nets usage in the context of E-learning.

1.4 Objective of the thesis

The main objective of the thesis is to reduce learning cost, provide flexible course delivery according to learners characteristics and behavior, gathers more efficient approaches for learning activities such as learning path sequencing, object recommendation and optimization of course delivery with the help of intelligent computing techniques which improve performance of learners.

The objectives of the thesis are described as follows:

- To perform an appropriate and extensive literature review pertaining to E-learning activities performed by various machine learning based intelligent computing methods such as Artificial neural network (ANN), Genetic Algorithm (GA), Swarm Optimizations, Data Mining (DM), Case-Based Reasoning (CBR), Semantic Web Services (SWS), etc. The combined review of various reported research work would help to identify untouched issues and relevant observations in the area of intelligent computing methods for E-learning.
- To develop an adaptive system which helps in facilitating the course content of different difficulty level to learners according to their needs, skills, knowledge and preferences. This will improve the overall learning performances of learners.

  This objective is achieved by following aims:

  AIM 1: To develop an adaptive CBR based e-learning system by considering different student features and improves their learning performance. Based on student features, learning material of different difficulty level provided to them to improve their syntax, logical and application-based programming error finding capabilities.

AIM 2: To develop an adaptive web based educational system which integrates a Hidden Markov Model (HMM) approach for prediction of future lecture topics or paths of Programming course that has been visited by learners as per their need and instructors provide assistance to them.

AIM 3: To improve the learning grades of learners on basis of their psychological and environmental factors using Hidden Markov Model. There are mainly two types of factors as positive and negative where Psychological and Environmental factors have been categorized. The performance of learners has been enhanced by involving Positive factors and the learning performance has been degraded with usage of negative factors.

- Identification and development of a modified threat driven modeling framework, which identifies the threats occurred during risk assessment phase and also intimate about their mitigation and correction before actual treatment. The Common Vulnerability Scoring System (CVSS) is used to rate vulnerabilities of different nature which further uses different metrics definition and perform calculation using distinguished normalized methods.
- To propose a new method to evaluate the performance of e-learning systems which includes importance (I), complexity (CC) and measurements of different learning problems and learning techniques. Performance Index (PI) is computed using I and CC corresponding to every learning model.
- Categorization of courses at different levels with the help of ontology by deploying the above mentioned for learning of C and Java Programming language using Protégé and packages, API, Java Interface and API.
- To make a comparative view in a tabular form of the above intelligent computing methods and its respective relative works by other researchers.

1.5 Plan of the thesis

This thesis has been divided into six chapters:

Chapter 1 consists of an introduction to the problem description followed by a comprehensive literature survey on E-learning from four perspectives: 1) Intelligent computing techniques in E-learning, 2) Semantic web and Ontology on E-learning based Services, 3) Use of Hidden Markov Model in E-learning, 4) Security in E-learning system using petri nets. In this literature survey our main concern is on the various problems of E-learning, intelligent techniques used and implementation reported by the different researchers. Tabular forms of comparative view of various intelligent computing methods with their salient features have been given in this chapter. Next the motivations to carry the present research out have been described. This is followed by the basic objective of this research. The research plan containing briefing of the work done in each chapter has been described.

Chapter 2 presents an introduction to the basic concepts of various intelligent computing methods used in the thesis such as Data mining, Case-Based Reasoning and ANN methods (Decision tree, Neural networks, Cases), Hidden Markov Model (HMM) with its application and usage in E-learning systems, Petri nets and their usages in security based e-learning system, and Semantic web technology with ontology and web services. This chapter also presents E-learning, learning theory, learning strategy and performance evaluation of learners.

Chapter 3 presents an adaptive CBR-ANN-DM based integrated method to provide learning material to student according to their needs at different levels of programming in computer science. This method has been deployed for the learning of C Programming language. This chapter describes the use of data mining and ANN methods for classification and categorization of learning content. ANN methods help in categorization and prediction of student features on basis of their performance. A novel feature of case-based reasoning is involved to represent the attribute value pairs of student features as cases in case base.

Chapter 4 and Chapter 5 presents a Hidden Markov Model based E-learning system which describes its two common perspectives: To develop an adaptive web based educational system using HMM for computer programming and to improve the learning performance of learners by predicting their psychological and environmental factors and enhance their learning productivity. This chapter also presents performance evaluation of methods and its comparison with other methods.

Chapter 6 presents a threat driven security framework using petri nets to remove the design vulnerabilities in system. The completeness and soundness of Aspect oriented stochastic petri nets models could be measured by proposed modified threat driven framework. Varieties of threat modeling phases like assessment of risk, mitigation assessment, attenuation description were added to propose modeling framework which enhance efficiency and accuracy of proposed model. The risk introduced in analysis phase measured by computing the occurrence of threats and their related impacts which are induced in system. The three behavioral properties of petri nets like boundness, reachability and liveness responsible for measuring overall correction assessment of proposed system.

Chapter 7 presents a novel way to evaluate the performance of E-learning system by considering the importance and complexity of learning problem and learning techniques involved in E-learning system. This chapter presents performance evaluation of proposed method and its comparison with other methods related to prediction accuracy, satisfaction degree, pre-post and learning standard methods.

Finally, Chapter 8 brings out the conclusion and contribution of the thesis together with the scope for future work in the area of intelligent computing methods for E-learning.

Chapter 2

Basic Concepts

In this chapter various methods and concepts definition, important features, functions, procedure and their solving methodology related to E-learning potential have been described. The chapter is organized as follows: Section 2.1 describes some of the intelligent and knowledge computing driven methods like Case Based Reasoning (CBR), Data Mining (DM) and Artificial Neural Networks (ANN). In Section 2.2 an introduction to Hidden Markov Model (HMM) with its application and usage in E-learning systems are presented. Simultaneously, some of mathematical modeling languages-based technique called Petri nets have been discussed with its usage in security-based e-learning systems. In Section 2.3 the Semantic web technology and Ontology based services are introduced. Section 2.4 presents E-learning and related concepts and finally Section 2.5 brings out conclusion of the chapter.

2.1 Intelligent and Knowledge Computing Methods

2.1.1 Case based reasoning (CBR)

CBR is used to solve new problems by reusing and retrieving existing knowledge which is obtained by learning previous experience about that domain. CBR is mainly useful for classification and data regression. The data input which is missing can be easily handled by strategy that governs CBR. In CBR, solution to new problem is obtained by storing old cases in the knowledge base. There are basic steps used to solve problems in CBR, which can be divided as: case representation, indexing, matching, adaptation and storage. The significance and arrival of new problem will be handled by case representation. After that, the new case features can be easily represented by indexing phase and similarity indexes are passed to matching phase. The cases which are similar can be retrieved by case matcher on index similarity from the case or knowledge base. Adaptation phase can adapt the solution of old problem so that new case problem can be easily adapted. Finally, after getting the solution of original or new problem the storage of new cases has been done in knowledge base which is confirmed later by storage phase of user (Aamodt and Plaza, 1994).

Every epoch of CBR can be identified by following four tasks i.e. retrieve, reuse, revise and retain. **Retrieve:** On the basis of given new problem or case similar indexing of cases could be retrieved from knowledge or case base. **Reuse:** The fetched or retrieved cases can be adapted to fit into new case problem. **Revise:** The solution has been evaluated and revised on basis of its working and throughput. **Retain:** Build decision whether to store the newly arrived case in case base or not.

Some of the advantages of CBR are: Easy knowledge acquisition, Learning from experiences, Ability to express specialized knowledge, Modularity, Self-updatability and Handling unexpected value and high inferential efficiency. Inspite of these advantages CBR also suffers from some problems i.e. High search cost, Case indexing problem, Adaptation knowledge should be domain specific, Inability to express generalized knowledge and Problem of competency.

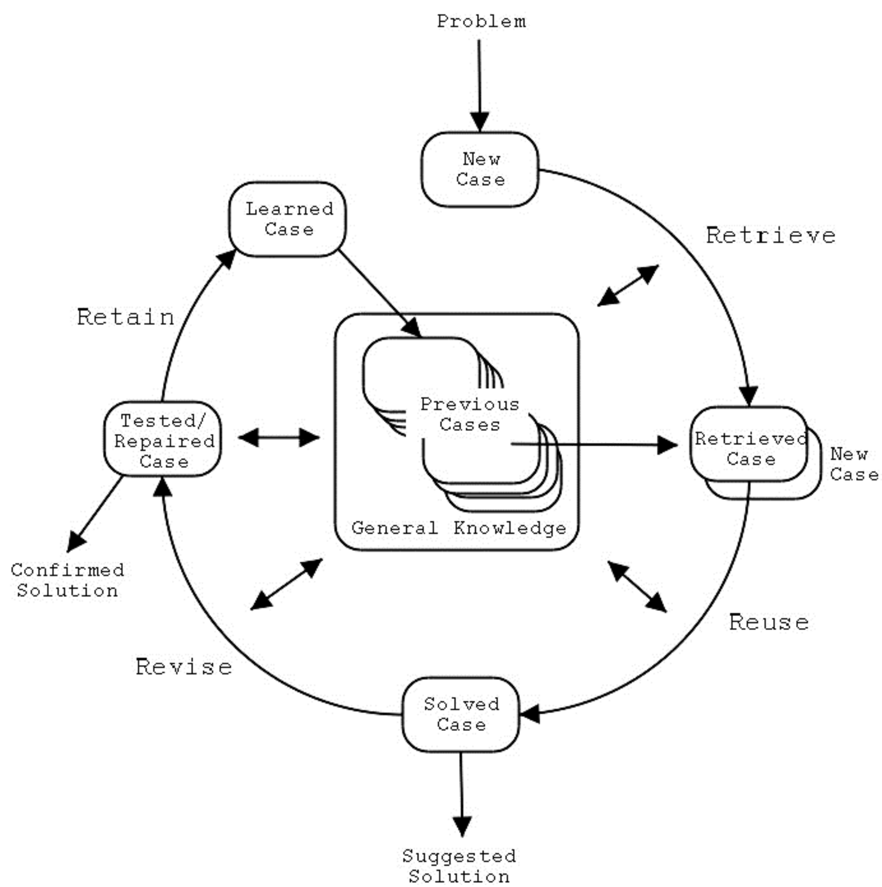


Figure 2.1 CBR cycle [4]

2.1.2 Data mining

Data mining is an intelligent computing technique which mainly used for analysis of big data sets with the help of advanced methods and tools. It is also defined as the method of identifying interesting patterns from large data set, where the information can be easily restored in warehouse or other useful storages.

It can also be considered as an iterative process where automatic or manual methods have been utilized for identification of progress in work. While carrying out the explanatory analysis data mining is more useful as there are no requirements of predetermined ideas regarding the probability of possible interesting outcomes. Data mining is the discovery for valuable and nontrivial information in huge amount of data.

In emerging area of intelligence there are two primary goals of data mining: predication and description. Predication mainly used for prediction of unknown, missing or future realistic values of different variable of background interest. Whereas description works on retrieving and describing important aspects of patterns that can be understood easily by human beings. Therefore, all concerned activities related to data mining must be categorized into these two as:

- Predicative data mining, utilized given data set to produce model of known
- Descriptive data mining generates new and nontrivial information on basis of given dataset.

On the predicative end, the prime purpose is to generate a model which can perform classification, estimation, or other similar tasks. Whereas, the purpose of descriptive mining is to forecast relationship among hidden patterns of large data sets which are stored in knowledge base. Data mining has been utilized in variety of important disciplines like medical, mathematical statistics, soft computing and machine learning. Data mining methodology has been deployed in diagnosis and treatment of various diseases in medical domain such as diabetes, heart disease detection, cancer detection etc. (Pandey and Mishra, 2009). With the analysis of ANCOVA and regression statistics analysis a comparison among two groups can be easily handled in data sets. In contrast, the soft computing and learning community has its relativity very higher when dealing with real world applications (Hastie et al., 2009; Witten et al., 2011).

The most common utilized methods/techniques in data mining are:

- **Decision trees:** To represent decisions such tree shaped structures are used. On basis of these decisions a set of vivid rules has been generated for particular data set. Varieties of specific decision tree methods are like J48 algorithm, C5.0, Classification and Regression Trees (CART) and Chi Square Automatic Interaction Detection (CHAID).

- **K-means nearest neighbor:** A technique used for classification of individual record of a particular data set on basis of different k records combinations which are similar to that particular class in stored dataset.

Decision trees (DT)

DT is a tool or model based approach used for generalization, categorization and classification of structured data. Decision tree managed to provide both predictive and classification-based functions simultaneously on same data set. With a sequence of questions and rules, data is classified (Chen et al., 2005). Major algorithms of decision tree analysis model include ID3, J48, C5.0, C4.5, CRAT and CHAID modeling techniques.

Decision tree usages

- Decision trees are used for data exploration
- DT used for data preprocessing
- DT used for prediction.

2.1.3 Artificial Neural Network

An artificial neural network comprised of individual processing elements which are known as neurons. Neuron is smallest unit of human brain. The neural network accepts input in the form of independent processing elements; each input element has certain weights also known as synapse which is feeded into network by summing them. The summated input also known as local induced field will be evaluated by activation function and external bias is added into network. The resultant input generates actual output which is compared with target output (Baylari and Montazer, 2009; Khamparia and Pandey, 2015). Once the error between actual and target output get minimized then at that instant network is fully trained and weights have not been further updated for particular designed network.

In Feed-forward neural networks only input layer and output layer are present. It is also known as single level perceptron model. The multi-layer network comprised of input, hidden and output layers. There can be N number of hidden layers present inside network due to that such architecture also known as multi-layer perceptron model. Finally, recurrent network is also similar to multilayer but in this network a feedback must be sent to input layer from output layer or output layer send feedback of resultant output to its preceding and following layers.

Salient features of ANN

- Adaptive learning, Self-organization, Real time operation, Massive Parallelism and Learning and generalizing ability.

Feed-Forward Back-propagation algorithm

Feed-Forward or multilayer perceptron is a supervised learning network which consists of three layers (input layer, hidden layer and output layer), each of which are fully connected. Feed-Forward networks that use differentiable function can use back propagation algorithm. This network guaranteed to converge only towards some local minima. Back propagation algorithm is a very common method for training multi-layered feed-forward networks. The error is calculated in this network between the actual output of the network and the output that was expected and the weights and threshold are then modified. There are various applications where back propagation neural network is used like character recognition, robotic arm application, segmentation of cancerous cell, usage of biometric card, digital signature identification.

Back propagation algorithm works in two phases: Propagation and weight updation.

The pseudo-code or algorithm has been mentioned for neural network training which comprised of Input, Output and hidden layer.

The network needs to be initialized with random weights

```
do
    For each given training instance: X
       Predicted = Net input – net output (network, X)  // Feed forward pass
       Actual = the target actually obtained using output and X.
       Error need to be computed at different output units of network
           Using backward phase further update weights from hidden layer to output layer
           Similarly using backward pass compute or updates the weight from input to hidden
       Updation of all weights of network except the input layer
  Until all training examples not classified correctly to distinct class or stopping criteria has been
reached
```

Finally, network has been updated with new weight vector and process has been terminated.

2.2 Hidden Markov Model (HMM) and Petri Nets

2.2.1 Introduction to HMM and characteristics

The variant and specific case of dynamic Bayesian networks are HMM which is used to model probabilistic sequence in a network and extensively used to solve problems in area of speech recognition, shape classification and E-learning systems. Two categories of distinct variables are stored in Hidden Markov model i.e. hidden state variable and observed variable. For representing such states which are not observed at any instant hidden states variables are preferred. In E-learning systems the major intent of HMM is by using last observations they need to draw probabilities of any particular state i.e. to personalize the web page content according to user's browser experience which can characterize the individual behaviour of user. In HMM, the current state must not be dependent on earlier observations sequences gave the previous states as per Markov assumptions. The parameters of HMM are represented by conditional probability which is estimated using previous state probability, current observations and necessary conditional probabilities (Mishra R., 2015).

The HMM model λ is represented by tuple which comprised of three symbols as $\lambda = \{A, B, \pi\}$, where A is the transition matrix, whose purpose is to define the probabilities between hidden states (N), B is an emission matrix, whose intent is to define the probabilities of M discrete observations under each state and π represents initial probabilities which comprised of stated vectors. The maximum occurrence of an event is adopted by classifier in which an unknown sequence O is provided to respective class which shows the maximum likelihood for an event to occur. It is represented as

Class (O) = argmax P (O| λ_t); here λ_t is the model with respect to the HMM t-th class. The probability term P (O| λ_t) can be calculated with the forward- backward procedure. There are some notations which are used to represent HMM model apart from various HMM based parameters.

T = It determines the total length of observation sequences which are presented to model.

N = maximum or total count of given states in model.

M = maximum or total count of observable symbols required for model.

$Q = \{q_0, q_1, q_2, q_{N-1}\}$ i.e. total number of distinct states present in model useful in Markov process.

$V = \{0, 1, 2…., M-1\}$ i.e. total possible observations.

Following steps are required to evaluate the model on basis of various estimated parameters which are explained as follow:

Step 1: Initialization of model with all HMM parameters, $\lambda = \{A, B, \pi\}$.

Step 2: Algorithm based on forward procedure or alpha pass parameters α_s need to be computed which determines the observational sequence of partial type using recursive computations up to finite amount of time t.

Step 3: Algorithm based on backward or beta pass parameters β_s determines the probability of the partial observation sequence from time s+1 to T-1 total recursive iterations.

Step 4: Computation of gamma parameters, i.e. γ_s.

Step 5: Computation of many gamma parameters if required which involves more than two variables.

Step 6: Model re-estimation using parameters $\lambda = \{A, B, \pi\}$.

Step 7: If probability of observations with respect to HMM parameter increases i.e. $P(O|\lambda)$ then move to Step 2. Else stop the procedure if $P(O|\lambda)$ does not increase beyond a threshold which is determined or which sets a limit to maximum number of iterations.

2.2.2 Fundamental Problems

There are mainly three fundamental problems which can be solved by using HMM technique (Latham et al., 2014).

Problem 1

Given a HMM based model as $\lambda = \{A, B, \pi\}$ and some series of observations O, we need to compute $P(O|\lambda)$ and determine that whether in existing model, is the probability or likelihood of observed sequence O can be computed.

Problem 2

Given $\lambda = \{A, B, \pi\}$ and an observation sequence O, for the given Markov model based process identify the most optimal state sequence i.e. there is need to remove out the hidden parts of the Hidden Markov Model.

Problem 3

An observation sequence O has been given with number of states and number of observation symbols, there is need to find out model $\lambda = \{A, B, \pi\}$ which maximizes the probability of O. Model has been trained according to data which has been best fitted among all dataset.

2.2.3 Comparison of HMM over Neural Network

HMM is a generative, probabilistic model where the Markov process which is generating the possible observation sequences need to be trained or how the observations or training data get distributed. Whereas, neural network is deterministic based discriminative model which performs mapping of patterns from input space to output space. Until the network gets trained completely, the weight gets updated or adjusted iteratively or minimum error achieved. For each input the response will be deterministic (Su et al., 2007; Deeb et al., 2014).

If we want to generate some meaningful word using neural network for which no grammatical structure or content provided i.e. hidden, then we need to train the network with initial word combination we have and what comes next in further iterations would be the same i.e. fixed. But, in comparison to HMM even if we fed the same initial word again then we will get less or more variations in output compare to neural network model.

2.2.4 Advantages and Disadvantages of HMM

Advantages

- HMM is graph based probabilistic model for which exact learning and inferencing is provided by existing algorithms.
- With the help of probability distributions HMM are able to represent the variance of applications over different model states.
- HMM is more effective and efficient probabilistic method compare to Bayesian networks.

Disadvantages

- HMM requires training using annotated data which is not completely automatic and also the size of training data is high.

- Due to Markovian nature of HMM, it does not take into account the sequence of states leading into any given state
- HMM can easily represent the distribution behaviour of finite states but fail to represent those states which are continuously varying with good accuracy.

2.2.5 Introduction to Petri Nets

Petri net is event driven tool used for modeling of discrete time driven adaptive systems. It is most widely used important tool which has ability to model different kind of real world systems. It is also called as bipartite directed graph which comprised of various objects: places, transitions and directed arcs which are used to connect places and transitions. Circle representation are used to denote places, bars going to represent smooth transitions and directed arcs used to connect places with transitions represented by an directed arrow. The directed graph comprised of Vertices (V) and Edges (E) or arcs in petri net model which are represented as:

$$G= (V, E)$$

$$V = P \cup T, \text{ and } P \cap T = \emptyset, \text{ Here P indicates finite places and T denotes transitions.}$$

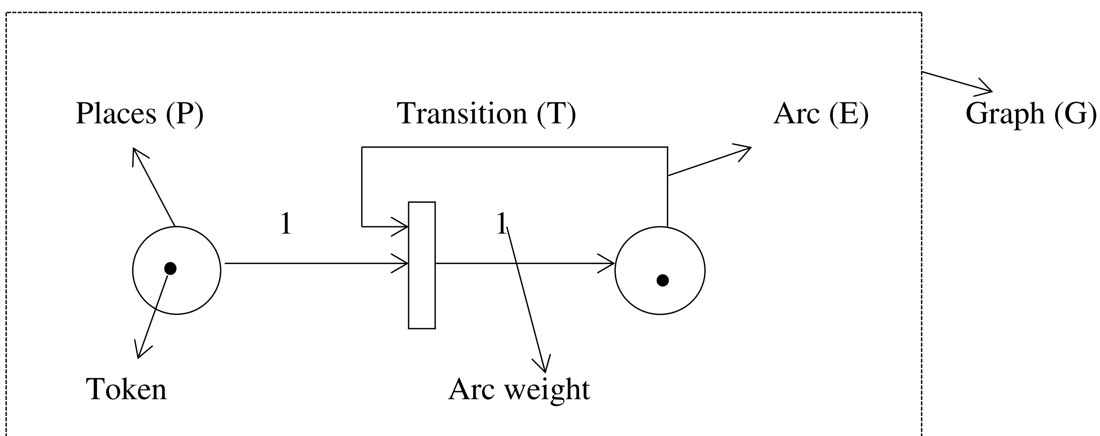


Figure 2.2 Simple Petri net model with markings

In petri model the count of tokens shown by number. The available number inside every circle, places, determines the count of tokens in those respective places. Like as shown in Figure 2.2, total two tokens are represented inside different places and these tokens numbers would change as a transition fires or an event get altered.

2.2.5.1 Places

Places are used to represent input or output area to the model. It is a kind of buffer arena used to initialize or accept tokens. These places have independent roles in variety of activities which are listed as follows:

- In telecommunication systems, it is acting as a medium like telephone lines, middleman, routers, hubs, switches etc.
- In hard disk, magneto tapes, conveyer belt, pins or queue it is acting as buffer.
- For identification of geographic location like place in office, clubs, hospitals, stores etc.

2.2.5.2 Transitions

Transitions are used to determine the various activities or events take place in the system. The perfect firing of transition can be done if it is enabled within stipulated time. Individual transition is represented as:

• An **event**: activity logged into database, transaction switching accidental activity happened with patient, traffic light switching mode.

• **An object modification to different form**, which introduces transformed product and update the field entries in database or updating the document level files which makes suitable view on objects.

• **Objects transfer**: moving objects or file from one end to other.

There are mainly two types of Transitions: Enabled and Fired Transition.

- **Enabled Transitions**

The transition (T1) in a petri net model is activated, when the total count of invoked tokens in the different places of inputs (P1 and P2) present in different location in model must be larger than the arcs weight which allows them to connect with transition T1.

- **Fired Transitions**

Transition will fire when all the pre-conditions are fulfilled for firing transition as it gets enabled. It means token must be shifted from one input place and keep it to another output place.

2.2.5.3 Arcs and Arc Weight

Arcs are used to connect place with transitions or vice versa. Arc is a simple connection which can acts as a link in communication and data transfer modeling. It can be acts as a bandwidth in media or used to model the mechanism of workflow management.

2.2.5.4 Tokens

Variety of input elements are denoted as tokens. After occurrence of events tokens being occurred and passed on to next portion. Tokens are also used as:

• **Physical objects**, like a customized product part, a part of a system, a manufacturing drug, any class object.

• **Information objects**, it can be considered as an email message, a field draft, any signal, a file, a packet, a data frame.

• **Objects collection**, the best illustrations are a vehicle that carries commodities for delivery, a data storage unit with different commodities, or location of a file object.

• **State indicator** denotes measure of the traffic signal, or the state of an object.

A signal indication from respective token determines whether given conditions are fulfilled by it or not. i.e. The next firing state world be that place where actually token could be seen.

Mathematical representation of a Petri net

An invoked model of petri net could comprise of four tuples which are represented as:

$$N = [P, T, I, O]$$

Here:

P indicates set of distinct places, $P = \{p_1, p_2, p_3 \ldots . p_L\}$, where $L > 0$

T indicates vivid transitions, $T = \{t1, t2, t3 \ldots t_m\}$, where $m>0$

$P \cap T = \emptyset$, the disjoint set of place and transitions.

$N \subseteq (P \times T) \cup (T \times P)$ is flow relationship indicates set of petri model.

$I: P \times T \rightarrow N$, indicates an input function which identifies directed arcs from P to T,

Where $N = \{0, 1, 2, 3, 4 \ldots\}$

$O: T \times P \rightarrow$ indicates an output function which identifies directed arcs from T to P.

A Petri net is given by (N, M_0), here N indicates Petri net model and M_0 denotes the marking done at an initial level. The initial symbol of marking is the number of token at the start of the model before entering to a firing state. Marking μ is responsible for allocation of distinguished tokens to different petri net places at μ = μ1, μ2, μ3 … μn.

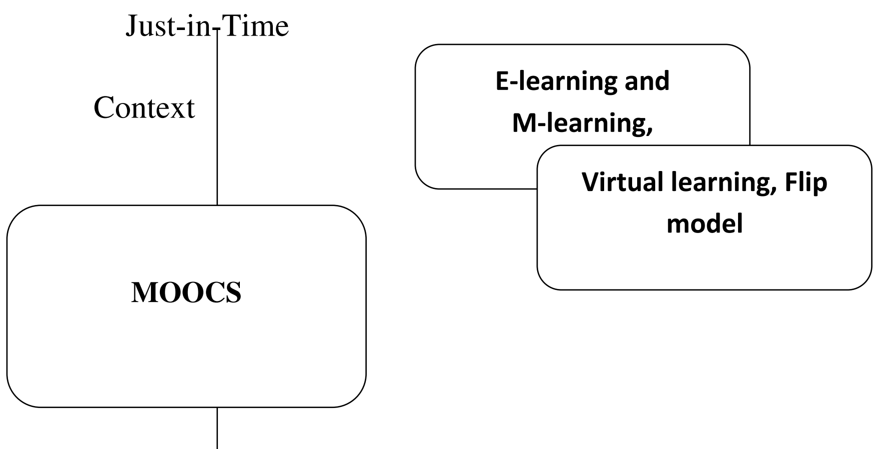
2.2.5.5 Petri net types

To enhance the modeling performance of petri net they are expanded to mainly three types: Timed Petri nets (TPN), Stochastic Petri nets (SPN) and Color Petri net (CPN).

- **Timed Petri nets:** For determination of time duration of system activities, normal petri nets models don't have mechanism to handle such activities. Timing parameter will solve the problem. For gaining a better sequence and model control, deterministic times are created through distinguished transitions.
- **Stochastic Timed Petri nets:** SPN is a model where distinguished transitions are related with a distributed random variable which indicates the required delay from the transition firing exponentially.
- **Color Petri net (CPN): Different types of colors are used to represent colored petri nets**. CPN is a well-organized and structured modeling approach for systems that comprised of different number of tokens or processes that tend to interact and synchronize at different levels. Various emerging areas exist where CPN is applied are nuclear safety system analysis, work flow analysis, automation and production systems.

2.3 E-learning

E-learning, a term introduced in 1999 during CBT system seminar is a way to learn and access emerging technologies through online interface and provides interactive or personalized training with the help of electronic media and widgets (Sahasrabudhe and Kanungo., 2014; Grigoras et al., 2014). (Hashim et al. 2014) defined E-learning as a platform that utilizes information and communication technologies as well as electronic media in terms of online learning, computer-based training etc.



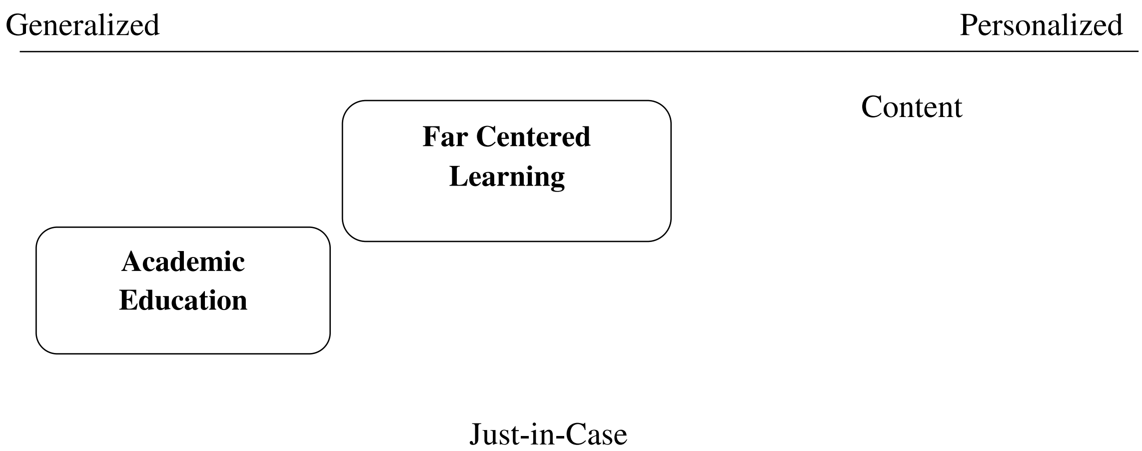


Figure 2.3 Relationship between E-learning and other learning methods (Drucker 2000)

Figure 2.3 shows the learning process and E-learning relationships in term of Place, Time, Personality and Centralization. The learning in Academic education is central, time place dependent and lack in personality. Distance learning allows some of personality and time independent by supporting multimedia streams within a border curriculum. CBT removes most of the limitations of time and location by providing the learning materials in portable form.

E-learning removes all limitations of time and location and provides high level of interaction, adaptive and personalization for the learners as well as the learning process (Drucker, 2000). The principle behind E-learning is that the pedagogy should match to curriculum, inclusion of learning content, innovative approaches, effective learning content, formative and summative assessment and learning should be transparent in its ease of use.

There are fundamentally two types of E-learning, namely Asynchronous and Synchronous E-learning. An Asynchronous E-learning means learning not at the same time usually allows learners to complete the assigned training at own pace without involvement of live video telecast. It provides flexibility to learner in information they need whenever they required it. Whereas, synchronous learning involves interaction of learners with an instructor in real time. Learners and instructor communicate with each other through synchronous media such as chat audio and videoconference support the synchronous E-learning.

Advantages of E-learning:

E-learning has distinct advantages over other learning approaches: E-learning allows selection of learning materials according to the learner's level of knowledge, interest, background skills and mental abilities. E-learning is cost effective and an effective way of delivering course content online anytime and anywhere. It is very convenient in which learners can work together and need not be depend on anyone for anything and can train themself from anywhere. Learners can share best knowledge with peers from different sources using optimized tools and architecture according to learning styles of different learners. The different models and encapsulated components with learning styles can be reusable and enables durability of components which could be reconfigured later according to usage. E-learning provides interoperability and flexibility of loosely coupled materials which allows developers to provides compatibility with other e-learning systems according to open e-learning standards and learning applications.

E-learning Standards:

With the growth on E-learning, the interoperability between different platforms and compatibility of the learning contents has been emerged. There are many organizations like IEEE learning technology standard committee (LTSC) and Advanced distributed learning (ADL) that have been making a big effort to standardize the learning contents, processes and other tools that are used in E-learning.

2.3.1 Learning Theory

Learning methodology depends upon theories which teach learners how to learn (Aimeur and Frasson, 1996). There are varieties of different theories existing but no such single theory able to deduce or inference information that whether all people or learner accomplished. Learning theories determined how participants or learners acquire, retain and recall existing knowledge through established set of learning principles. Through these principles how learning could occur better using learning theories. These theories of principles used to identify instructional media, techniques, tools and emerging strategies that re-invent collaborative learning through various mediums. Learning process or theories based on observable changes in behavior of learner where based on new response learner could accomplish new behavioral changes. To improve the diversity of learning theories three different learning models and associated approaches have been encountered as behaviorist approach, the cognitivist approach, the humanistic approach and the constructivist approach which improves learner experience (Merriam et al., 2012).

Behaviorist Approach: This approach mainly focused on how the learning behaviour of learner changes which had impact on their learning skills. It assumes that the learner is essentially passive responding to the environmental stimuli. Therefore, the behaviorist gives emphasis more on skill development and innovative abilities of learner rather than storing knowledge somewhere.

Cognitivist Approach: Cognitive theories are deals with knowledge which governs experience. Learning process occurs through internal processing of learning information. The information is already known, available or stored within memory is easily understood by learner through cognitivism which divides hierarchy of schema and changes through generalization and specialization.

Humanistic Approach: Humanistic theories are concerned with the development of human potential, dignity, and worth. The learning in this approach will occur in an environment in which learners are happy to implement new and emerging ideas without any effect or problem cursed by external facts or figures.

Constructivist Approach: Constructivist based on internal experiences and individual knowledge to develop or construct information on basis of learner skills rather than depending on others. Learning is based on how individual learner interpret meaning of information and experiences based on facts and axioms explored by their efforts with help of instructor guidance which enhance their project efficiency on data which was gathered or collected.

2.3.2 Learning Styles

Learning style plays an important role in process of learning. Many of the individuals involved different learning styles to make decisions and solve different learning problems. Among different proposed learning styles, few theories of Kolbes, Five factor and Silverman is being suitable for computer assisted applications applicable for e-learning and m-learning environment. Felder Silverman learning style was one of the most popular learning style used in computer Assisted applications which considers four dimensions for learning style: Active/Reflexive, Visual/Verbal, Sensing/Intuitive, Sequential/Global. Fleming introduced VARK learning style model which categorizes learners to four different groups: Visual (V), Aural (A), Reading (R) and Kinesthetic (K). Myers and Briggs proposed a different type of indicator known as MBTI which was based on Jung's personality theory and used frequently for educational purpose. This type of learning style categorizes into four different functions: Extraversion/Introversion (E/I), Sensing/Intuition (S/I), Thinking/Feeling (T/F) and Judging/Perceiving (J/P).

2.3.3 Performance Evaluation of Learner

Evaluation means testing which refers to broad range of tasks including observations, presentations, group study in a continuous, comprehensive, systematic and purposeful process which provides fruitful insight to learner to enhance their training and learning. Planning for student evaluation is an important part of instructor teaching which starts from gathering data about learner, instructional media, taking feedback from learner and provide motivation or counselling to learner which improves progress and overall learning outcome of learners through different learning approaches. The evaluation of learner's performance is classified into three classes depending on their purpose: Earlier, formative and summative.

Earlier Evaluation: Such kind of evaluation leads instructor to choose learning content, establish learning objectives, address logistic and personalized issues of learner, design suitable atmosphere in classrooms which enhance participation of learners and makes learning more interactive to produce productive results from learners.

Formative Evaluation: With continuous process of learning or giving instruction this evaluation goes on. It is useful in analyzing learning materials, instructors effectiveness during teaching, and students learning achievements. It is a building process of combining several individual learning components of new learning materials, skills, goals into single meaningful problem. Its main purpose is to catch learning deficiencies which allows learners to master their skill set and knowledge through several learning interventions rapidly in convenient manner.

Summative Evaluation: It occurs mostly at the end of learning to determine the achievement of learner which he/she was collected with help of formative evaluation. Summative evaluation incorporates quantitative kind of assessment focuses on learning outcome at end. It is used to assess whether the obtained result of learning object, experimenter, instructor, persons etc. met the stated goals.

Chapter 3

Case Representation and Retrieval in CBR for E-Learning

3.1 Introduction

Now days, e-learning plays major role in education. With the rapid growth of Internet technology many e-learning applications are developed and used (Chang, 2009; Cheng, 2011; Wang, 2011). E-learning system helps students to search learning material as per their need. These systems are called adaptive system. As per many literatures these systems provide efficient and accurate learning material as per user requirement and thus enhance the knowledge efficiency and effectiveness of learner (Wang, 2009; Tseng and Liao, 2011; Huang and Chen, 2007; Liu and Yang, 2005). The e-learning system has major two components e-learning content repository and inference engine. The user submitted its request in terms of his characteristics such as anxiety, motivation, learning level, gender, cognitive ability etc. to inference engine. Then inference engine retrieves the content available in e-learning repository and provide it to the learner as shown in Fig.3.1(a). In this chapter, we have described case-based reasoning (CBR) strategy for inference engine of e-learning system (Rodrigues et al., 2007; Salem, 2005; Tseng et al., 2008).

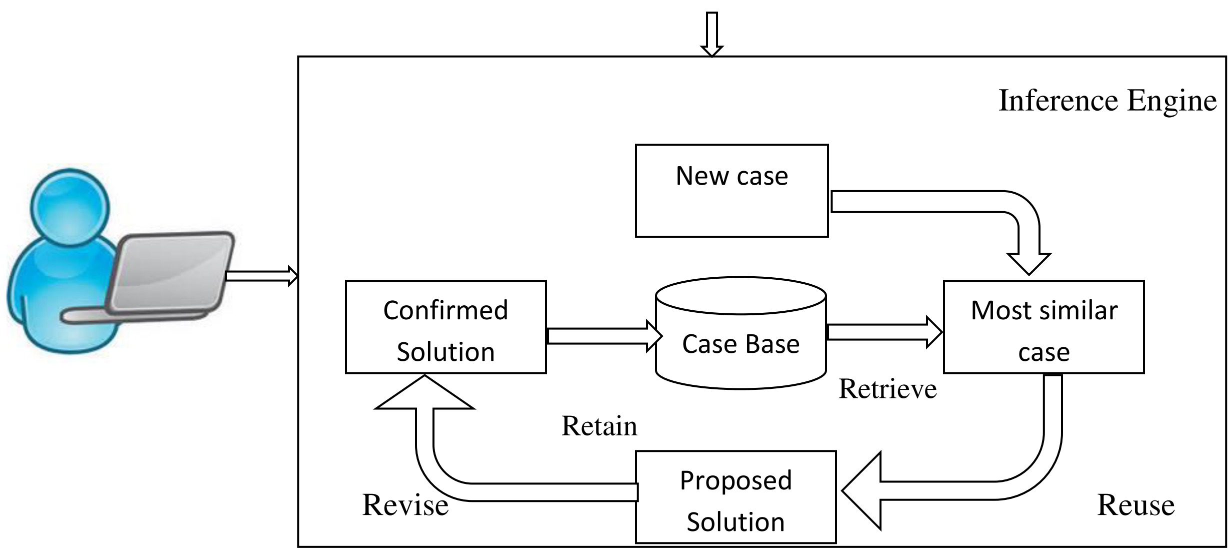
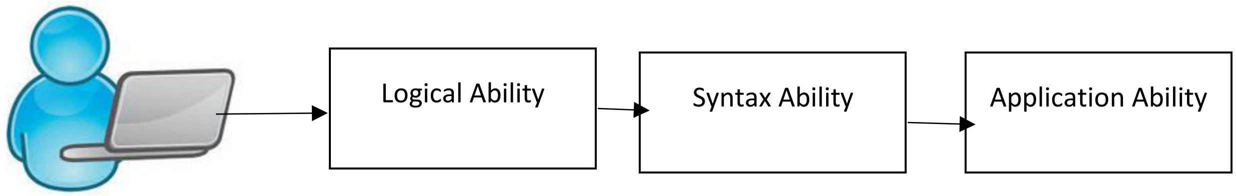


Fig 3.1 (a) Architecture of Inference Engine

Basic understanding of any programming language in computer science, consists of a good understanding of logic, syntax and applications. A good programmer has a good sense of logic as well as syntax of the programming language. Development of a good program requires a good knowledge of logic as well as syntax, but first and foremost requirement is the logical ability. Therefore, it is required that first learner should enhance his logical ability. After logical ability, second requirement is to enhance the syntactical knowledge of the programming language. The last requirement is to deploy logical and syntactical knowledge to develop an application. So, this is phase wise development of learner as shown in Fig. 3.1 (b).



Learner

Fig. 3.1 (b) Learner Development

If student is weak in logic building, then he will not able to implement the program and finally he won’t be able to develop an application. If in the beginning student’s logical weakness is identified (logical level) then their efficiency can be remarkably improved rather than the weakness is identified at implementation (syntax level) or development level (application level).

In any case-based reasoning system the main component is case base. The performance and effectiveness of inference engine completely lies on the way cases are stored in the case base. In earlier CBR based systems, the cases are stored as set of problem and solution. The problem consists of attributes which has some value. The biggest challenge is that these values of attributes are some fixed value which doesn’t lie in range for example, if a case consist of features such as age, temperature, headache, body-ache then the value is 32, 96, yes, yes respectively.

The stated work is published in: Khamparia, A. & Pandey, A novel method of case representation and retrieval in CBR for e-learning in B. Educ Inf Technol (2017) 22: 337. https://doi.org/10.1007/s10639-015-9447-8.

But there is possibility that age and temperatures should be in range such as 5<age<15 and 96<temperature<100. The traditional CBR system doesn’t deal with this situation. The main contribution of this chapter is to develop an e-learning system that deals with the above stated situation. In this chapter, CBR based adaptive e-learning system is developed which uses ANN and Data Mining for classification of learning styles.

3.2 Methodology

This section explains the various steps and computing methods performed to develop an adaptive system for teaching computer programming course and deliver the learning material to learner (student) according to learner characteristics.

- In the first step, the data was collected data, which consists of all student features.
- In Second step ANN model was deployed to identify the student features and learning performance relationship. Then data mining technique is used for classification of student features.
- Finally, case-based reasoning was deployed for classification of e-learning content based on student characteristics.

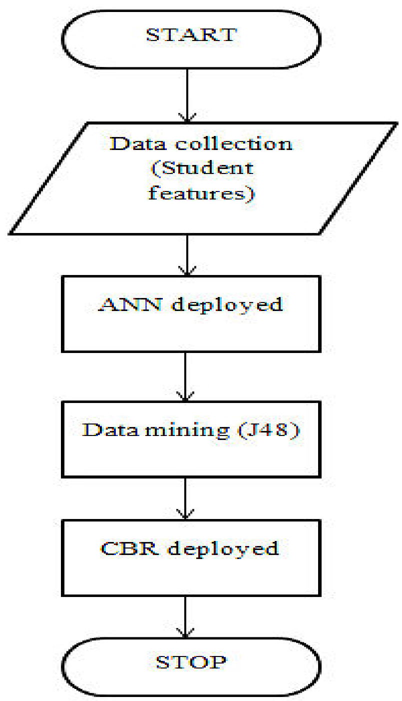


Figure 3.2 Systematic Process

3.2.1 Student Features

Student characteristics like: gender (G), anxiety (A), personality (P), learning (L) and cognitive ability (C) affect the learning performance of student (Wang et al., 2009). These features affect the student learning performance in computer domain also. Therefore, in this work, we have considered these features to measure the learning performance of students in C programming domain. In this work, we have grouped features in various levels such as: G into male (M) and female (F); A in low (L), medium (M) and high (H); P in introvert (IN), mildly introvert (MI), Neutral (N), mildly extrovert (ME) and extrovert (EX); L in Thinking & belief (TB), Perception of information (POI) and Watching & listening (WAL) and C in Field dependent (FD) and Field Independent (FI).

3.2.2 Experimental Sample

The data of 100 students have been gathered from Asian Pacific University. A questionnaire based on C programming language was given to these students to predict their Syntax (SY), Logical (LG) and Application capability (AP). The programming questionnaire evaluate the student capability for SY, LG and AP. Test assessment was performed in two steps: mid-term (after 7 weeks) and end-term test (after 14 weeks) each consisted of 20 questions for each SY, LG and AP.

This study deployed the Foreign Language Classroom Anxiety Scale (Horwitz and Cope, 1986) to measure the level of Anxiety of students participating in test study. In this scale the scores are computed based on Likert range that ranges from 33 to 165. The students having scores in the range of 33 to 66 were classified as low anxiety (LA); in the range of 67-132 were medium anxiety (MA); and in the range of 133-166 were classified as high anxiety (HA). Ganschow and Sparks (1996) categorized the students into introverted (IN), mildly introverted (MI), neutral (N), mildly extroverted (ME) and extroverted (E) according to the scores obtained from extroversion scale (Eyesenck, 1964). Students having scores from 24 to 60 were classified as I; from 61 to 69 as MI; from 70 to 87 as N; from 88 to 96 as ME; and from 97 to 120 are classified as E. Sarasubm (1998) grouped the learning process into Thinking & belief (TB), Perception of information (POI) and Watching & listening (WAL) on the basis of introversion scale. The student’s cognitive style were classified as field dependence (FD) and field independence (FI) (Witkin et al., 1977).

The e-learning content of C programming language was divided into three levels: SY, LG and AP. Each of these contains questions or code snippets related to syntax, logic and application-oriented domain. The students were taught with this e-learning content and their post-performance was evaluated using post-test.

3.3 Artificial Neural Network (ANN) model and Data Mining (DM)

ANN with back propagation algorithm (BP) was used due to its extensive use and better result in many applications (Dayhoff, 1990). ANN was used to find the relationship between student features and learning performance. The data collected from students was divided into training and testing set for ANN.

The ANN model has five nodes corresponding to five students features: G, A, P, L and C in input layer (Eyesenck, 1964; Horwitz and Cope, 1986; Sarasubm, 1998; Witkin et al., 1977). The input values for these characteristics were coded as following: Gender: M =1, F = 2; Personality type: I = 1, MI = 2, N =3, ME =4, and E=5; Anxiety level: LA=1, MA=2, HA=3; Learning: TB=1, POI=2 and WAL=3; Cognitive level: FD=1, and FI =2. For example, at any time one input which was given to ANN consist of {G, A, P, L, C} values. There were three output nodes corresponding to SY, LG and AP in output layer, which represents the learning performance. The output of ANN corresponding to SY, LG and AP is High (H), Medium (M) or Low (L) depending upon the difficulty level. Table 3.1 shows the result of partial combination of student characteristics and learning performance levels. The feed forward BP network was trained upto 100 epochs with momentum 0.001 and learning rate from 0.001 to 0.3. In input layer TRAINLM was used for training, in the hidden layer TRANSIG function was used. Hit and trial method was used to obtain best architecture. Table 3.2 lists various BP models, showing that model 5-7-3 (input nodes-hidden nodes-output nodes) was selected as it produced the best result.

Table 3.1 Partial combination (Dataset) of student characteristics with learning performance levels

Gender (G)	Anxiety (A)	Personality (P)	Learning (L)	Cognitive (C)	Syntax (SY)	Logical(LG)	Application (AP)
1	1	1	2	2	M	M	H
1	1	2	1	2	H	M	H
1	2	2	3	1	M	L	L
1	1	2	3	1	L	H	M
1	1	3	3	2	L	M	H
1	1	4	1	1	L	L	L
1	2	5	1	2	H	M	M
2	1	1	3	2	M	M	H
2	1	3	1	1	L	L	M
2	1	3	3	2	H	H	H
2	1	3	4	1	H	M	M
2	1	4	2	1	M	L	L
2	3	5	1	1	H	L	L
2	2	5	1	2	H	H	H
2	3	4	2	2	L	H	M

Table 3.2 Various options of Back Propagation mode

BP model	RMSE	
	Training	Testing
5-2-3	0.0560	0.0676
5-3-3	0.0583	0.0422
5-4-3	0.0340	0.0292
5-5-3	0.0375	0.0040
5-6-3	0.0307	0.0040
5-7-3	**0.0232**	**0.0002**
5-8-3	0.0248	0.0052

J48 algorithm was used to classify the students as per their features (Patil and Shreker, 2013). We have deployed the J48 algorithm because it deals with missing or NULL values in the preprocessing stage and then the tree was pruned. J48 builds a univariate decision tree from the dataset using concept of information gain by entropy. It finds the difference in entropy and the attribute having the highest normalized information gain was used to make decision. It produced rules and decision tree for data classification and characterizes student learning features. Figure 3.3-3.5 represents decision tree for SY, LG and AP at various levels and classified on the basis of different student features. This tree was used to generate the rules.

The J48 algorithm was implemented using Weka tool. The collected student data consisted of 100 records and 5 attributes (student features) in which 50 records were used for training, rest of the 50 are equally divided test and validation set. Detailed description of data set is given in Table 3.3.

Table 3.3 Detail of dataset

Attributes	**Data type**
Gender	Categorical (Male, Female)
Anxiety	Categorical (High, Medium, Low)
Personality	Categorical (High, Medium, Low)
Learning	Categorical (High, Medium, Low)
Cognitive ability	Categorical (High, Medium, Low)

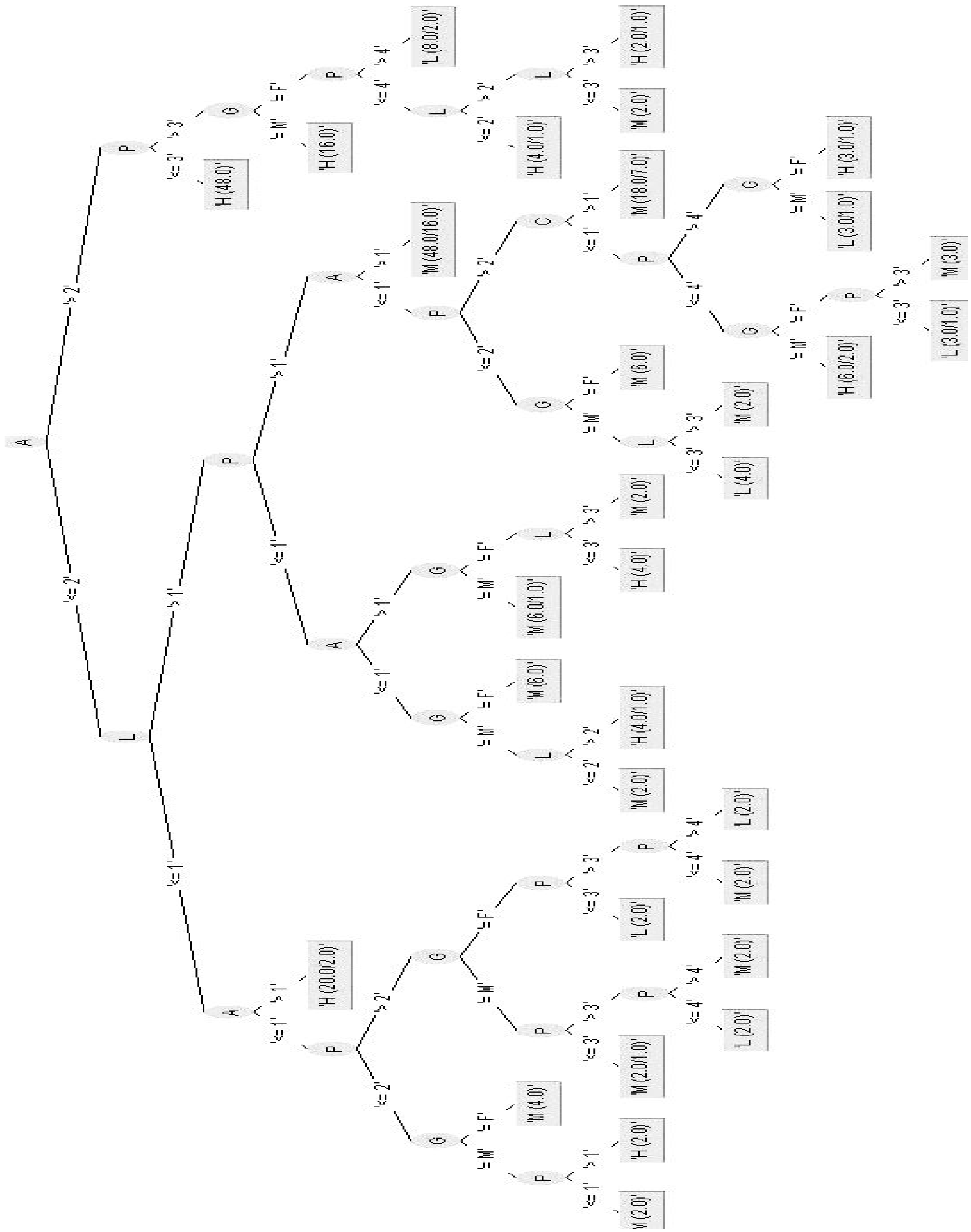


Figure 3.3 Decision tree for SY

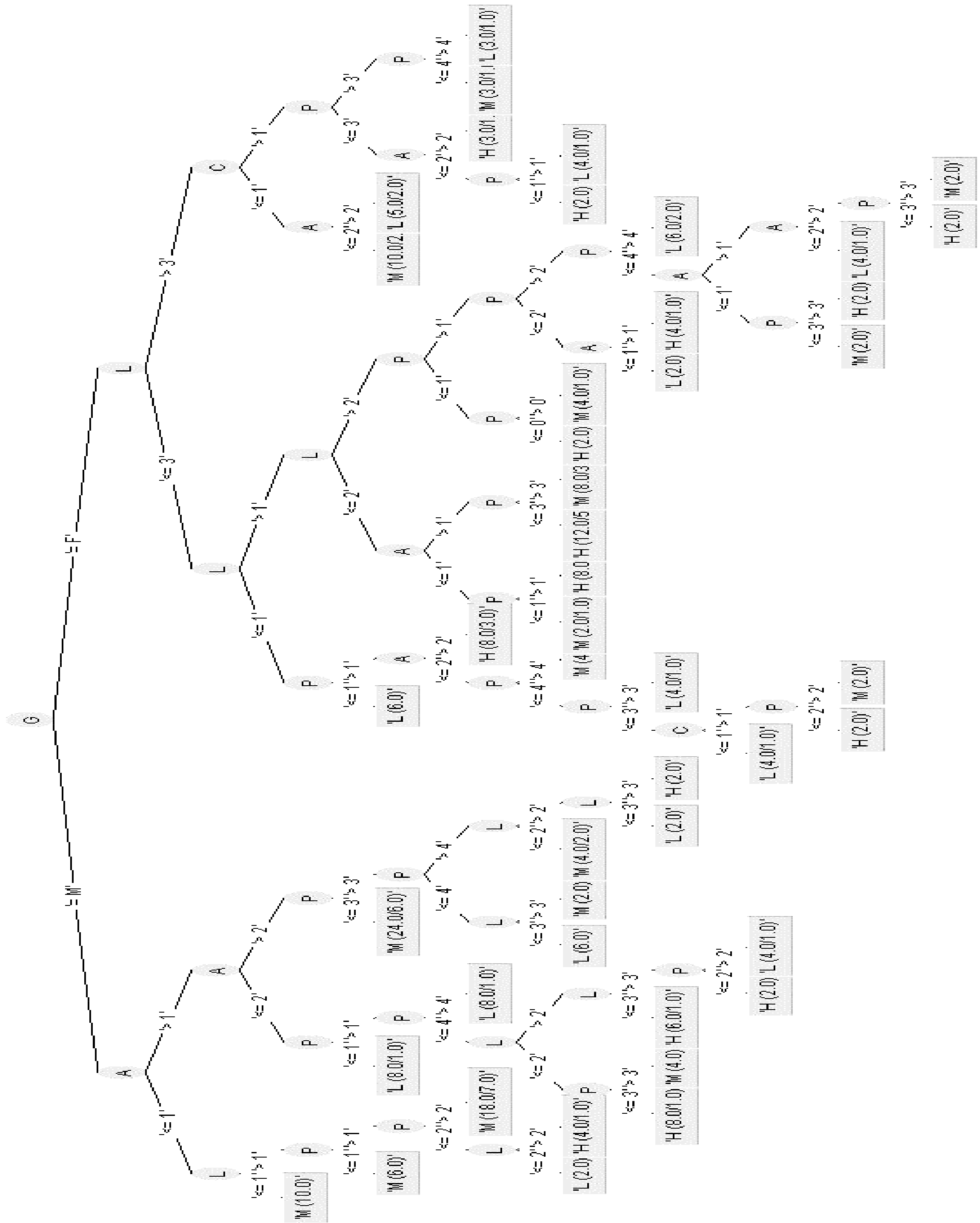


Figure 3.4 Decision tree for LG

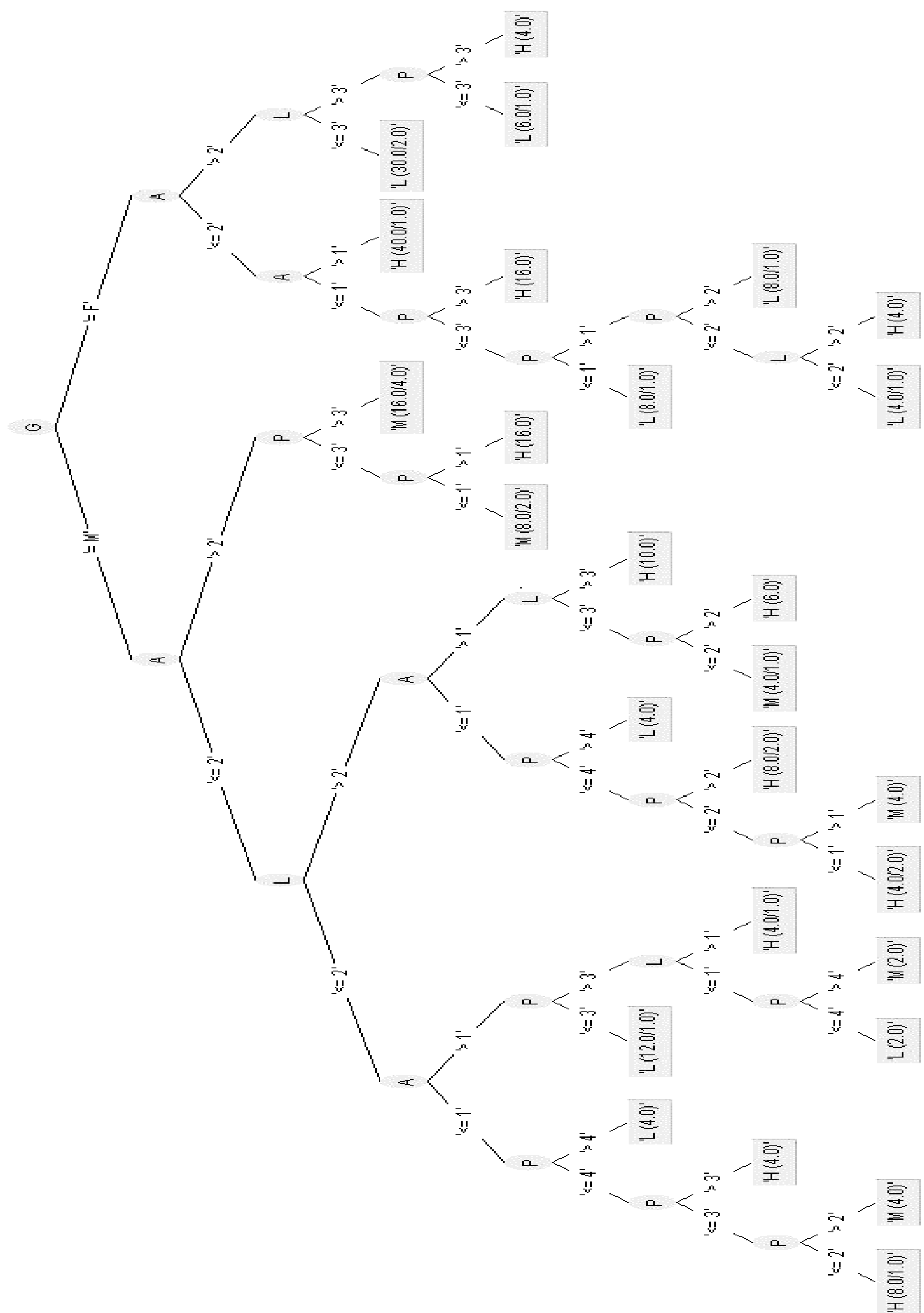


Figure 3.5 Decision tree for AP

3.4 CBR Model

As described in previous Chapter 2 the various processes in the CBR model are described below with reference to its implementation for personalized e-learning system. The CBR model mainly consists of knowledge acquisition, representation, storage, retrieval, and adaptation which have been described in the context of personalized e-learning system as given below.

3.4.1 Knowledge representation and Acquisition

The knowledge was represented via attribute (feature) vector and stored in the tabular form as shown in Table 3.4. The knowledge was acquired through dialogue session as shown below:

3.4.1.1 Psychological based parameters (attributes)

Psychological parameter consisted of Gender (G), Anxiety (A), Personality (P), Learning (L) and Cognitive ability (C).

Gender

Is the learner Male (M)?

Is the learner Female (F)?

Anxiety

Is the anxiety Low (L)?

Is the anxiety Medium (M)?

Is the anxiety High (H)?

Personality parameters

Is the personality Introvert (I)?

Is the personality Mildly Introvert (MI)?

Is the personality Neutral (N)?

Is the personality Mildly Extrovert (ME)?

Is the personality Extrovert (E)?

Learning style

Is Thinking & belief (TB) learning style used by learner?

Is Perception of information (POI) learning style used by learner?

Is Watching & listening (WAL) learning style used by learner?

Cognitive style

Is Field Dependent (FD) cognitive style used by learner?

Is Field Independent (FI) cognitive style used by learner?

3.4.2 Case Storage

Cases in a case base were represented using attribute value pair. Each attribute (features) consisted of bit of string where the number of bits depends upon the level of attributes. Cases were stored in tabular form i.e. input matrix and output. Following steps were used to represent attributes of input matrix.

All the main five parameters (attributes) as given in Table 3.4 i.e. gender (G), anxiety (A), personality (P), learning parameter (L), Cognitive style (C) are represented by string of binary numbers where the number of bits used to encode each feature or attribute is only for the purpose of matching. For example, gender has two values i.e. M and F, so gender attribute is represented using two bits 01 for male and 10 for female. Similarly, personality has five levels: IN, MI, N, ME and EX. Therefore, personality attribute is represented by string of 5 bits. IN represented as ($1*2^4+0*2^3+0*2^2+0*2^1+0*2^0$), MI represented as ($0*2^4+1*2^3+0*2^2+0*2^1+0*2^0$), N represented as ($0*2^4+0*2^3+1*2^2+0*2^1+0*2^0$), ME represented as ($1*2^4+0*2^3+0*2^2+1*2^1+0*2^0$) and EX represented as ($0*2^4+0*2^3+0*2^2+0*2^1+1*2^0$). Anxiety has three levels: low, medium, high. Therefore, anxiety attribute is represented by string of 3 bits. LA represented as ($0*2^2+0*2^1+1*2^0$), MA represented as ($0*2^2+1*2^1+0*2^0$) and HA represented as ($1*2^2+0*2^1+0*2^0$). Learning style has three levels: TB, POI and WAL. Therefore, learning style is represented by string of 3 bits. TB represented as ($0*2^2+0*2^1+1*2^0$), POI represented as ($0*2^2+1*2^1+0*2^0$) and WAL represented as ($1*2^2+0*2^1+0*2^0$). Cognitive style has two levels:

FD and FI. FD represented as $(0*2^1+1*2^0)$ and FI represented as $(1*2^1+0*2^0)$ whereas null represented as 00 (Ø) as shown in case 1 of Table 3.4.

The data of ten cases are shown in Table 3.4. In Table 3.4 the first column represents the number of cases, rest of the columns from 2-7 represents the student features or attributes. The last column represents output for SY as Medium (M), High (H) and Low (L). Column 3-5 further subdivided into two sub columns headed by lower bound (LB) and upper bound (UB). Every attribute was represented in form of bits according to student features.

LB and UB has been assigned to attribute based on range value generated from decision tree. For example, as shown in Table 3.4 for case 1, if A has range lies in A<=1 i.e. it has only LB but UB is not applicable for this case. So, its LB is categorized as 001 and UB as NA. In case 3, if A has range lies in A<=1 i.e. it has only LB and UB is not applicable. So, its LB becomes 001 and UB is NA. In Case 6, P attribute has LB 00100 and UB as 01000 where both are applicable for case 6. In case 5, for P attribute its range lies as 4<P<=3. So LB and UB both are applicable for this case as a result its LB will be 00100 and UB will be 01000 respectively.

For example, in first case i.e. SY (M).

The value of G: The gender for first case was considered to be male i.e. 01.

The value of A: This case has only LB but no UB and anxiety was low so LA will be 001.

The value of P: This case has only LB but no UB and personality was extrovert (I) i.e. 00001.

The value of L: This case has only LB but no UB and learning was TB i.e. 001.

The value of C: This has not considered cognitive style for same so it was 00 i.e. Ø.

Table 3.4 Case base for SY

Cases	Gender	Anxiety		Personality		Learning		Cognitive	Output (SY)
		Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound		
1	01	001	Not Available	00001	Not Available	001	Not Available	00	Medium

2	01	001	Not Available	00010	Not Available	001	Not Available	00	High
3	10	001	Not Available	00010	Not Available	001	Not Available	00	Medium
4	01	001	Not Available	00100	Not Available	001	Not Available	00	Medium
5	01	001	Not Available	00100	01000	001	Not Available	00	Low
6	01	001	Not Available	00100	10000	001	Not Available	00	Medium
7	01	001	Not Available	00010	Not Available	010	100	00	Low
8	10	001	Not Available	01000	Not Available	001	Not Available	00	Medium
9	10	001	Not Available	00100	10000	001	Not Available	00	Low
10	01	010	Not Available	00001	Not Available	010	100	00	Medium

3.4.3 Case Retrieval

New cases are matched with case base in a case base using following formula.

$D_j = \sum_{i=1}^{n} Decimal\_Value(S_{ij})$ ----- (3.1)

Where j is the jth case and D_j is summative difference of new case with j^{th} cases.

Where S_{ij} is calculated in two ways:

1. When the lower bound (LB) and upper bound (UB) of attributes not exist.

   $S_{ij} = AC_{ij} \oplus NC_i$ ------------- (3.2)

   Where AC_{ij} is an i^{th} attribute of j^{th} case in a case base and NC_i is an i^{th} attribute of new case. Where $\oplus$ represents bitwise XOR operator. We have used XOR because it is a bitwise comparator.
2. When lower and upper bound of attributes exist.

S_{ij} = min $\{(LBAC_{ij} \oplus NC_i), (UBAC_{ij} \oplus NC_i)\}$ --------- (3.3)

Where $LBAC_{ij}$ is lower bound of an ith attribute of jth case in a case base, $UBAC_{ij}$ is upper bound of an ith attribute of jth case in a case base and NC_i is an ith attribute of new case.

3. If summative difference (D_j) for more than one cases in a case base with new cases are same then following formula is used for selection of best matched case (BMS).

S_{ij} = max $\{(LBAC_{ij} \oplus NC_i), (UBAC_{ij} \oplus NC_i)\}$ ---------- (3.4)

3.4.4 Case Adaptation

In this work, case adaptation was used to reuse the solution of retrieved case. In copy adaptation method the solution of retrieved case was used to solve new case without any modifications.

3.5 Implementation

In this study, we have developed a Java based learning system for selection of student characteristics and predict the difficulty level of learning material. MySQL server was used to promote the fast and secure access from the web application. Hyper Text mark Up Language and Java scripts were used in the client side and Servlet and Java Servlet Page were designed using Eclipse IDE and used in server side. The typical implementation of application using Java is shown in Figure 3.10. The system was implementation four steps: In first step, collection of data was carried out in term of student features, in second step Artificial Neural Network was deployed to identify student features and learning performance relationship. The ANN was implemented using neural network toolbox of MATLAB. In third step, J48 was applied for the classification. In last step, Case-Based Reasoning was used for classification of learners on the basis of their features.

3.5.1 Generate Binary Value Generated Case (BVGC)

First, user has selected the features of student as shown in left most part of Figure 3.10. Then the BVGC was generated corresponding to the user selected criteria (as mentioned in step 1). For example, the new case generated corresponding to the user selection was: {F L ME TB Ø} where Ø denotes the NULL value and corresponding BVGC was {10 001 01000 001 00}. This new case was matched one by one with all the cases in a case base using equation 3.1-3.3.

For example, the difference with case 8 (when no lower and upper bound exist for A, P and L) was calculated using equation 3.4 as shown in Figure 3.6(c) and 3.6(d) respectively. The smallest value of D_j for new case was 3 (with case 8) as shown in Figure 3.6(a). Therefore, the new case was similar to the case 8. Hence, the difficulty level of SY for new case was M (using copy adaptation). Similarly, the level of LG and AP were computed as shown in rightmost part of the Figure 3.9.

Case 8: **{10 001 01000 001 00}** **New case:** **{10 001 01000 010 00}**	**Case 7:** **{01 001 00010 010/100 00}** **New case:** **{10 001 01000 010 00}**	**Case 9:** **{10 001 00100/10000 001 00}** **New case:** **{10 001 01000 010 00}**	**Case 10:** **{01 010 00001 010/100 00}** **New case:** **{10 001 01000 010 00}**
Applying XOR $\oplus$ {00 000 00000 011 00} Therefore $D_j = 3$	Applying XOR $\oplus$ {11 000 01010 000/110 00} Therefore $D_j = 3+10+0 = 13$ Where left side of ("/") shows lower bound and right side shows upper bound in case 7.	Applying XOR $\oplus$ {00 000 01100/11000 011 00} Therefore $D_j = 12+3 = 15$	Applying XOR $\oplus$ {11 011 01001 000/110 00} Therefore $D_j = 3+3+9 = 15$
(a)	(b)	(c)	(d)

Figure 3.6 Computation of XOR; (a) computation of XOR between 8th case and new case; (b) computation of XOR between 7th case and new case; (c) computation of XOR between 9th case and new case; (d) computation of XOR between 10th case and new case

The pseudo code for generating BVGC is shown in Figure 3.7.

```
Procedure_Conversion (Value)
Input variable: Gender (G).
Value: Male (M) and Female (F).
Begin
     If (attribute is G and Value = 'M') then
     Set G = 01
     Else
     Set G=10.
End
```

Figure 3.7 Pseudo code for binary string generation of G.

3.5.2 Retrieval

The retrieval consists of two steps: matching and selection. The BVGC i.e. new case is matched one by one with all the cases in a case base using equation 3.1-3.3. After matching the case in case-base the case with smaller distance is selected as most similar case to new case. The pseudo code for matching and selection is shown in Figure 3.8 and 3.9.

```
Procedure_Matching (BVGC, Case_j)
Input: BVGC[m] (an array containing the binary string of G, A, P, L, C where); case_j[m]. where case_j is
the j^th Case in a case base , n is no. of cases in case base and m is number of attributes.
Output: XOR[n] where n is no. of cases in case base.
Begin
For j <-1..n
    For i <-1..m
            While (length (BVGC [i]) <= length (Case_j[i]))
        Compute XOR[j][i] = XOR (BVGC[i], Case_j [i])
        End While
    End for
End While
End
```

Figure 3.8 Pseudo code for Matching

```
Procedure_Selection (XOR [][])
Input: Computed XOR[n][m] for new cases where n is number of cases in a case base and m is
number of attribute for each cases
Output: smallest value of D_j where D_j is summative difference of new cases with j^th cases; BMS: Best
matched case
Begin
For j<-n
    For i<-m
    Compute D_j = Σ_{i=1}^{n} Decimal_Value(XOR[j][i])
    End for
End for
Compute min( D_1, D_2, ... ... .... D_n)
BMS <-j
End
```

Figure 3.9 Pseudo code for Selection

3.5.3 Case Adaptation

Case adaptation is as described in Section 3.4.4

3.6 Result

Results are generated on basis of input and output values. The first stage is selection of attribute or feature vectors for generation of BVGC as shown in left most part of Figure 3.10 where out of all attribute pairs one attribute can be selected using drop down list. In the next stage the selected attributes are displayed as new user case as shown in the middle most part of Figure 3.10. Then BVGC is generated according to attribute type. The right most side of the Figure 3.10 shows the output in terms of SY, LG and AP i.e. according to individual personality what content type of programming level should be provided to it according to his needs and preferences. Medium (M), Low (L) or High (H) content was selected as per requirement.

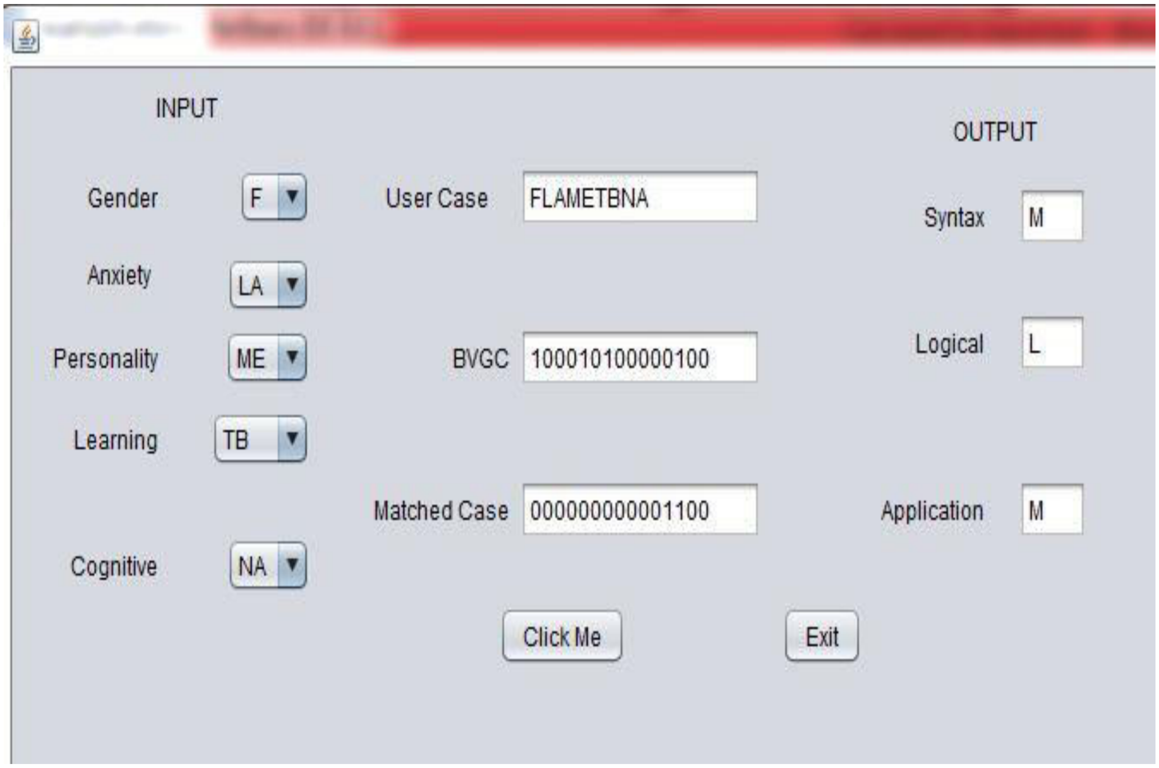


Figure 3.10 GUI for Student characteristic selection and predicting difficulty level of material

3.6.1 Empirical Experiment Results

The effectiveness and feasibility of proposed system was validated on the basis of survey on different students after deployment of CBR system. Students of class size 100 **were** assigned to experimental and control group whose size consisted of 50 students respectively. With usage of programming constructs and mean score obtained it depicted that control group students were facing difficulties. Whereas students of experimental group adapted e-learning system which consisted of different students features. Later, after successful programming practice performed by students of experimental group once they mastered error removal in current level they applied for individual knowledge level test which once got approved. After successfully completion of current level they have proceed to next level and generate the appropriate learning path for performance improvement of learner.

Multiple choice questionnaire-based pre-test was given to experimental and control group for testing homogeneity of system. Individual syntax and logical based questions carries 1 marks each and total questions would be 20 for each type. For identifying AP usage feasibility 20 different questions on loops, conditional statements, switch cases etc. being provided to make program for different applications out of which 8 questions of lower level based on conditional statements, 8 questions of higher level based on loops and remaining 4 questions were based on control transfer structures. Each question counted for 2 marks, for total of 40 marks. SY pre-test identification showed that mean (M) and standard deviation (SD) of experimental group was 22.56 and 4.02 respectively. For control group M and SD values were 23.79 and 5.25 respectively. The independent sample t-test between these two group was t = 1.3153 and p value = 0.1915, indicating that there was no significant difference between these two groups in identifying or recognizing SY error. In LG error section experimental group had M and SD values 23.46 and 3.22 respectively; the control group M and SD values were 23.57 and 3.99 respectively. The t-test result showed (t = 0.1517, p value = 0.8797) no significant difference between two groups in LG error findings and mistake committed from students of both groups. For AP feasibility, experimental group M and SD values were 14.12 and 6.54 respectively whereas control group M and SD values were 14.92 and 7.63 respectively. The t-test result indicated (t =0.5629 and p-value = 0.5748) no significant difference between two groups in this section. After 16 weeks of C programming learning course students from both groups were compared in post-test. The post-test results indicated that for SY error identification, the experimental group M and SD values were 32.57 and 3.44 respectively, while the control group M and SD values were 28.44 and 4.56 respectively. The t-test result showed significant difference (t = 5.1126, p-value=0.0001<0.01) between two groups in SY error section. For LG error, the experimental group M and SD values were 30.14 and 3.72 respectively; the control group M and SD values were 23.99 and 3.94 respectively. The t-test showed significant difference (t = 8.02 and p-value = 0.0001<0.01) between two groups in LG error section. For last section the experimental group M and SD values were 22.43 and 5.22 respectively and control group M and SD values were 15.95 and 6.32 respectively. The t-test result showed significant difference (t = 5.5899 and p-value = 0.0001 <0.01) between two groups in application feasibility section. The results demonstrated that in SY, LG and AP feasibility section of post-test, the mean score of experimental group were slightly higher than mean scores of control group. It means C Programming CBR based e-learning system is better than regular learning course. Student from Asia Pacific region need to follow online adaptive learning system so that they can master programming concepts, inference new knowledge, remove SY and LG errors & permit programmers to use feasible application and enhance their learning performance. Figure 3.11 and Figure 3.12 demonstrates results of pre-test and post-test individually for different sections where experimental group performs better after post-test conducted by instructors of C programming. Figure 3.13-3.15 shows the individual comparative means of pretest and post-test with respect to SY, LG and AP levels.

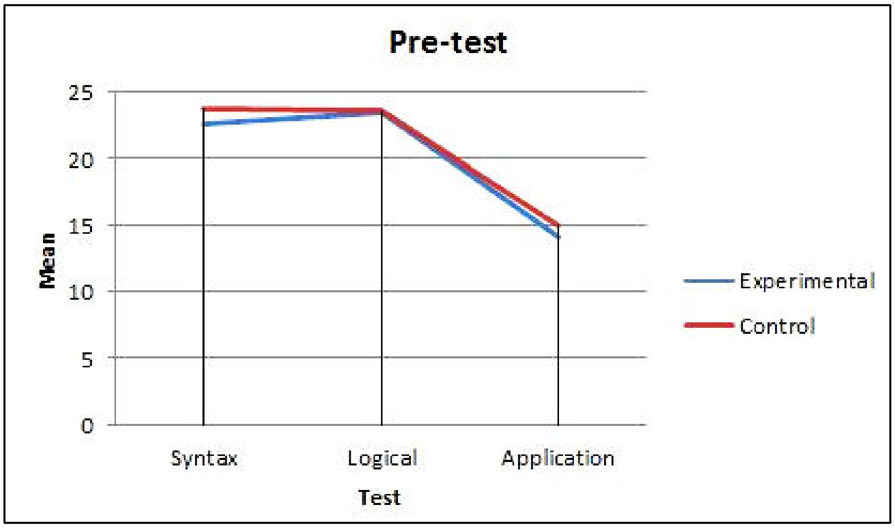


Figure 3.11 Pre-test analysis

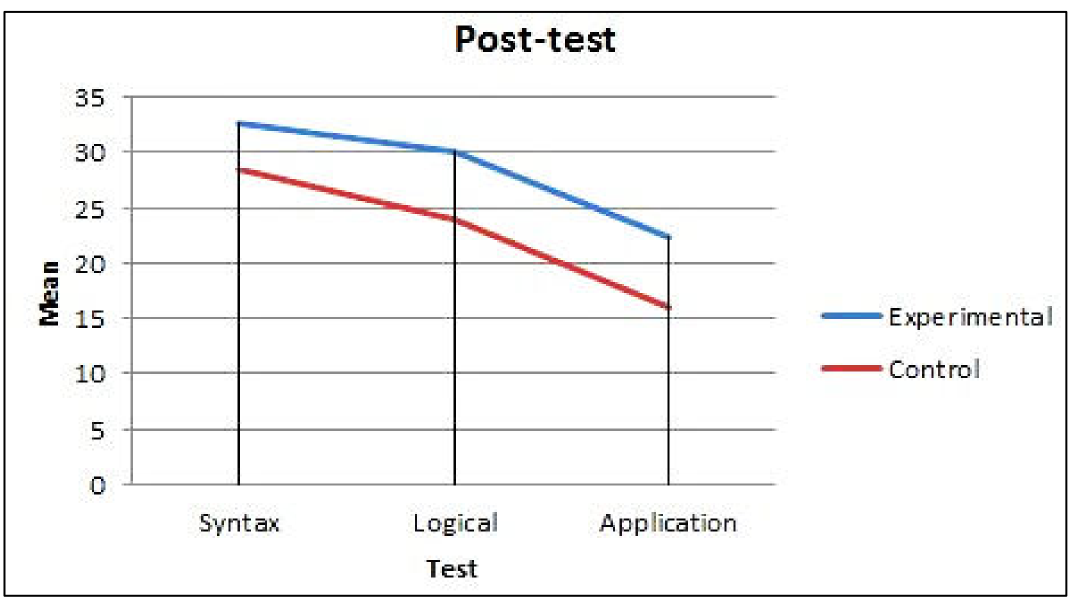


Figure 3.12 **Post-test analysis**

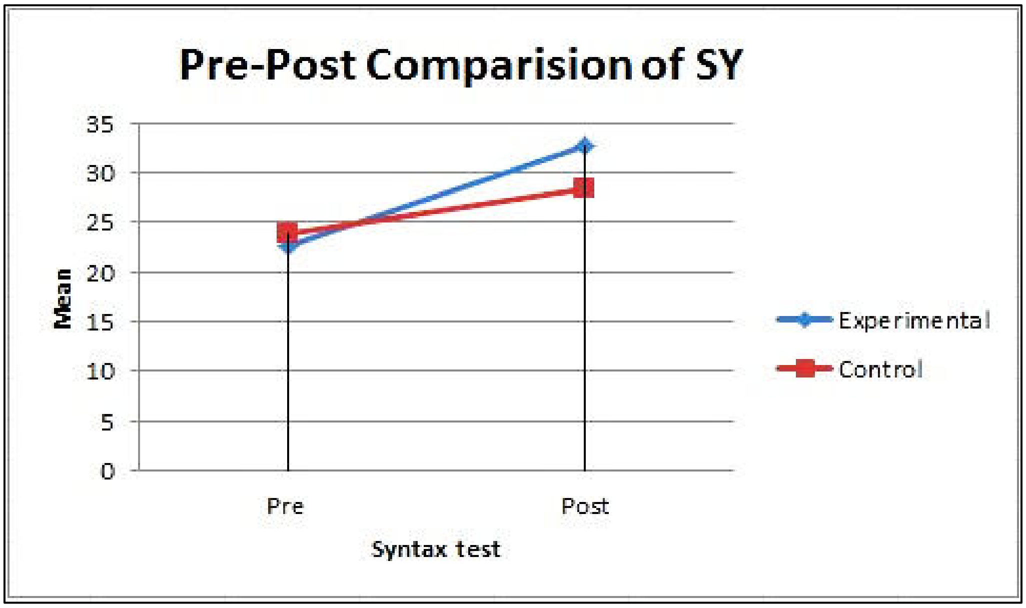


Figure 3.13 Syntax analysis

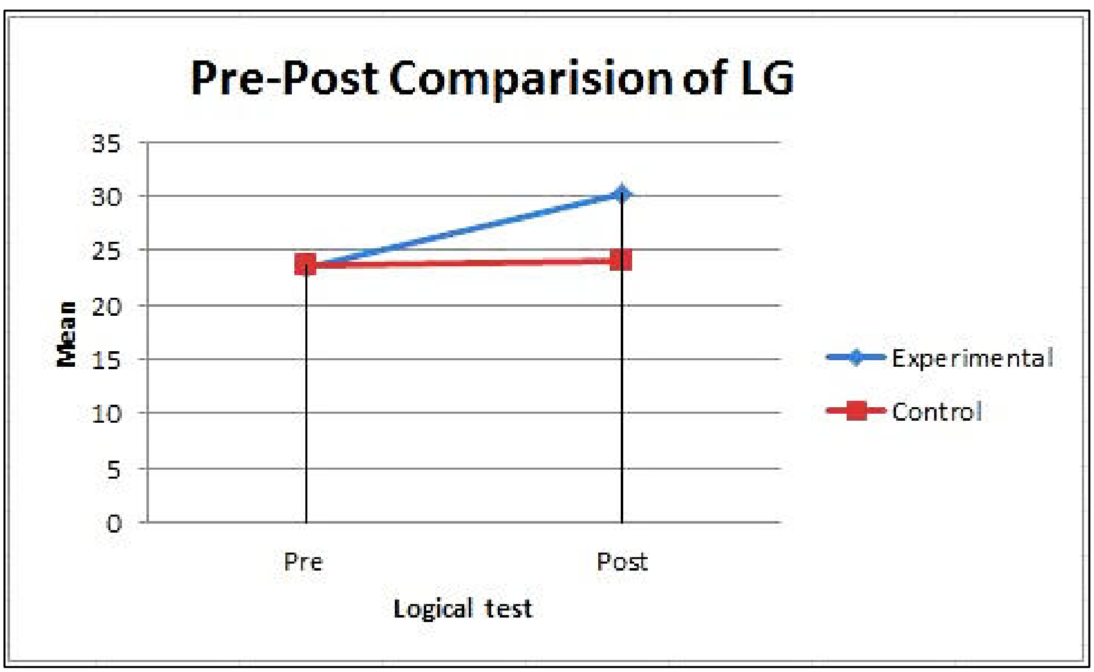


Figure 3.14 Logical analysis

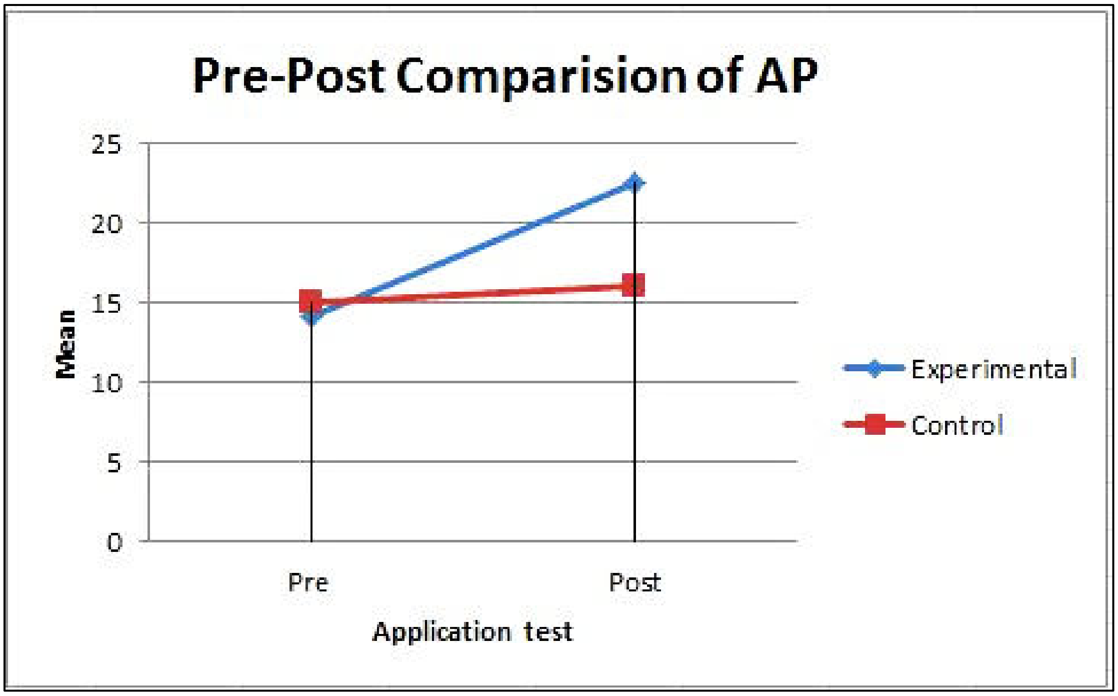


Figure 3.15 Application analysis

3.7 Related works and Comparative view of methods

To compare the proposed work extensive survey was conducted in the following areas: Adaptive learning, sequence of learning, student characteristics, DM, decision tree and Case based reasoning.

The benefit of adaptive learning system is that it offers flexible solutions by dynamically adapting learning content depending upon the individual learner's need. (Trantafillou and Demetriadis 2003) developed a system based on hypermedia in which various categories related to cognitive abilities were considered for improving students learning ability. (Huang and Chen 2007) developed responsive generative e-learning system which involves genetic behaviour to perform adaptive testing of the learner's requirement. (Wang and Liao 2009) proposed an adaptive system based on decision tree for optimizing learning sequences for given course content. (Wang and Liao 2011) developed a multi-adaptive system for teaching English. The system explores e-learning content (vocabulary and grammar) with comparison of results of individual student groups of different categories. (Chookaew et al., 2012) developed an e-learning environment for adaptive courses. It provides sequence of the content to learners based on their knowledge and learning styles.

In addition to adaptive and personalized technique learning path sequence is also equally important to enhance learner's performance through e-learning content. (Chen et al., 2006) proposed web driven system which utilizes item driven response theory and provides sequence of course content based on capability and content difficulty which faced by learner. (Carchiolo et al., 2002) have developed a web-based learning environment for generation of adaptive personalized learning path based on student's profile.

(Yang et al., 2008) have developed Multi-Dimensional Personalization Criteria System to provide content based on different characteristics of learners which utilizes cognitive abilities and distinguished variations of Silverman style. (Seters et al., 2012) distinguished student's through their level of motivation, background knowledge and demographic abilities which further analyze strategies and related features needed for behavioral improvement.

(Hsia et al., 2006) used DM for identification of several choices adopted by students of different categories. (Romeo and Bra, 2007) used DM for enhancing course effectiveness of learner and formulate and identify different relationships which relies on student's characteristics. (Chen and Hsu, 2007) preferred DM for integration of different values on the basis of different relationships and their casual effects which effects learner performance. (Despotovic-Zrakic et al., 2010) differentiates students into different clusters with assignment and usage of learning styles i.e. Felder-Silverman.

(Chen et al., 2000) used DT and data cubes to improve learning behavior of student's and performance. (Hsu, 2008) developed a recommendation system which removes English language learning problems of demographic student's. (Lin et al., 2013) used DT for integration of game-based learning with various learning styles which later demonstrates different sequence of learning.

(Gilbert and Han, 1999) proposed CBR system, which dynamically maximize the improvement in learning behaviour on the basis of previous learning experience. One of such system called PERSO utilizes CBR to determine the best course based on the student's knowledge level and preference. (Pandey et al., 2014) proposed CBR based adaptive system which utilizes student features and provide most appropriate learning content to individual on the basis of their learning preference and adaptive needs.

A detailed summary and comparison of the present work has been shown in Table 3.5. Most of the researchers in algorithmic method uses Artificial Neural Network, Data mining and GA etc. and do their deployment in Java platform.

Table 3.5 Comparative view of methods

Author	**Student features**	**Problem/Technique**	**Discipline**
Yang et al. (2008)	C and LS	Personalization/ Pre and Post-test analysis	Computer science course
Wang and Liao (2009)	G, P and A	Personalization / ANN, Data mining	English learning System
Wang et al. (2011)	G, P, C, LS and SG	Adaptive learning sequence / Data mining	English Language
Seters et al. (2012)	G, SL, SPK and IM	Adaptive path sequence / Pre and Post-test analysis	Molecular biology course
Our approach (2015)	G, P, A, LS and C	Personalization, Path sequencing / ANN, Data mining and CBR with Pre-Post-test analysis	Computer Programming Course

* C indicates Cognitive, LS: Learning Style, G: Gender, A: Anxiety, P: Personality, SG: Student Grades, SL: Study level, SPK: Student prior knowledge, IM: Intrinsic motivation

3.8 Conclusion

In this chapter, an adaptive Case-Based Reasoning based e-learning system was developed by considering various characteristics and prolific features of students which improves their performance of learning. It enables students to develop their learning with personalized features. Based on the students Gender, Anxiety, Personality, Learning Level and Cognitive nature, variety of distinguished learning material has been presented to students which improves their ability of finding Syntax, Logical and Application oriented error identification capabilities. The individual performance of different students is explored with usage of data and web mining techniques, Artificial Neural Network and Case-Based Reasoning as the core of adaptive e-learning system. For reduction of rule base data different symbolic neuro-oriented rules will be introduced in future which removes the drawback of maximum rule generation. There are other modes of programming like complexity of algorithm, situation to solve problem strategies, memory usage etc. are not incorporated in proposed work due to avoidance of computational burden limited programming aspects related to Syntax, Logical and application are covered. Future scope will consider other important features and more number of related aspects to programming.

Chapter 4

Hidden Markov Model Based E-Learning Systems

In this chapter we have described Hidden Markov Model (HMM) governed e-learning systems in two perspectives: 1) To develop an adaptive web based educational system using HMM for computer programming and 2) To improve the learning performance of learners by predicting their psychological and environmental factors and enhance their learning productivity.

4.1 Introduction

With the invention and growth of WWW technologies, latest gadgets in past decades have emerged into latest e-learning trends and possibilities. Internet enabled learning has shifted the education from the teacher centered to learner centered. Traditional web-based system put the static learning material on the web and does not delivered the learning material to individual learner based on his attributes, background experiences and demand. There is a need to build adaptive intelligent system which represents goals, interests, skills, preferences, intellectual ability of learner or student and update it with respect to their information or facts acquiring ability and adapt the content to student needs (Wang and Liao, 2011). These systems are able to predict student future learning actions, next path sequences to visit based on their current and previous knowledge base or information to improve their accuracy and performance. In our C programming-based e-learning system we have three modules: Course module, Instructor module and student module. In course module, all the lectures and course content of programming has been organized which are divided into several concepts depend on topic coverage (Tseng et al., 2008).

Instructor module has three functions: 1) uploading the course content; 2) Providing learning path sequence; 3) providing assignments and evaluating students. In this system, HMM works as an instructor for providing learning path sequence and evaluating students. Student module allows students to interact with different course content i.e. lectures as well as instructor to resolve their problems. The status of student knowledge related to lecture component is computed with the help of prediction model known as Hidden Markov Model (HMM).

HMM are used to predict the future student actions and improves the discussion and lobbing of lecture material on the basis of every student needs. The use of HMM in learning task is to find the best set of transmission and emission probabilities on basis of given set of sequences. The purpose was to derive the maximum likelihood estimate (using Baum-welch) of parameters of HMM given the sequences. HMM is a probability-based model which analyzes the dataset on basis of generalization from available given sequence (Mishra R., 2015). HMM generates finite possible states which are connected by arc or transitions and produce an observation sequence which depend on its bias and probabilities. HMM is commonly used in speech and gesture recognition, bioinformatics and Internet enabled learning systems etc. HMM is performed in internet enabled English language learning system to deliver the adaptive material like tenses, Verb, Passive-Active voice to student's groups according to their needs. Based on the browsing action of individual learner different course materials can be fetched with help of HMM model. HMM predicts efficient stranded protein genes available in DNA sequence of eukaryotes.

In this chapter, we have proposed an adaptive web-based e-learning system based on HMM approach which predicts the future actions and next lecture content of C programming to be visited by student based on history of lecture contents and delivers the learning material according to their ability and preferences. The organization of the work as follows. Section 4.2 represents the proposed methodology. Section 4.3 deals with implementation and Section 4.4 discussed system evaluation in comparison to perceptron model and finally Section 4.5 brings out the conclusion.

4.2 Proposed Methodology

We have implemented the complete in three phases: Starting, Intermediate and Final. Data has been collected from events recorded in web-based e-learning system. Our proposed system able to facilitates student of university with help of faculty module in which student able to interact with faculty at other site. The complete procedure for prediction of student actions using HMM is shown in Figure 4.1.

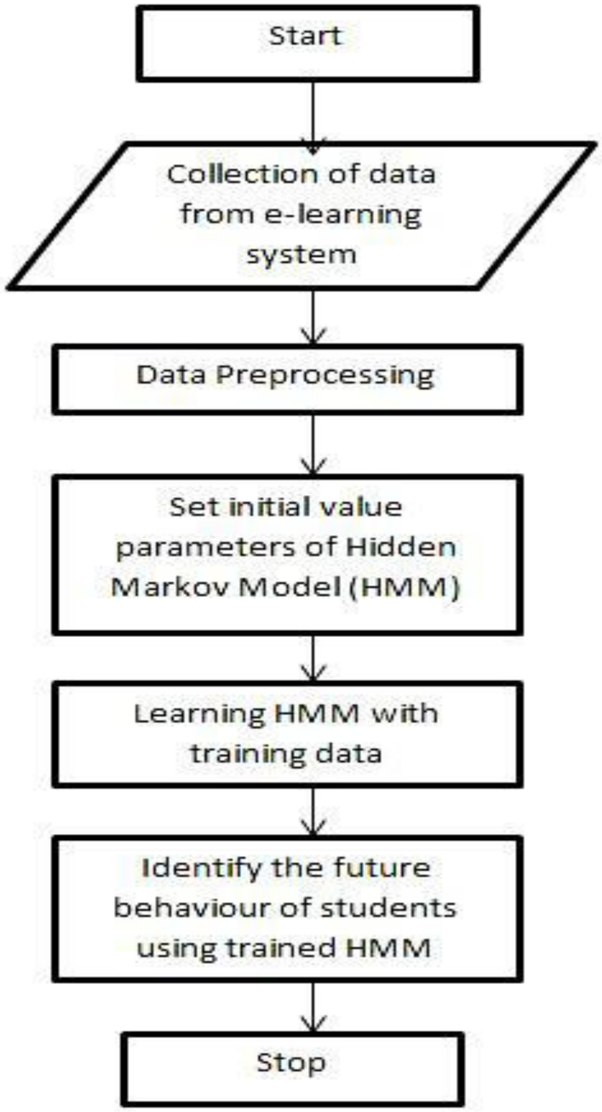


Figure 4.1 Proposed Approach

In starting phase, for every students a HMM (λ) was developed which focused on their old lecture content access sequence as shown in Figure 4.2. First time the learning path sequence for any learner was prescribed by expertise.

HMM is specified by:

N, the number of hidden states

L= $\{L_0, L_1, L_2 \ldots L_{N-1}\}$ denotes the count of lectures in the system model, q_t specified hidden state at time t.

M represents the number of observable states with $V = \{V_0, V_1 \ldots . V_{M-1}\}$ the set of observable symbols and O_t the observation state at time t.

$A = \{a_{ij}\}$ the transition probabilities between hidden states L_i and L_j.

$B = \{b_j(k)\}$ the probabilities of the observable states V_k in hidden state L_j.

$\prod = \{\pi_i\}$, the initial state probabilities.

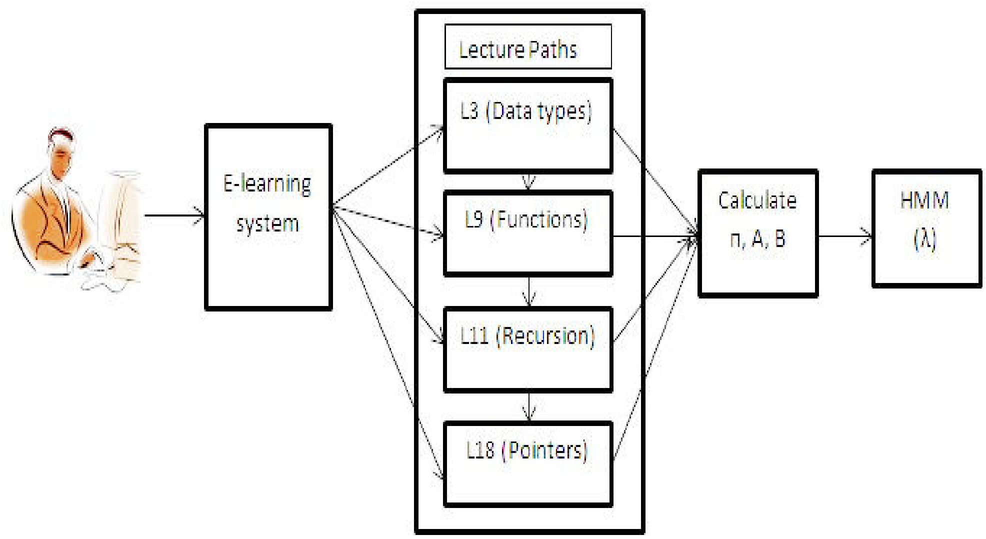


Figure 4.2 Starting phase of HMM

In the intermediate phase, we have used Baum Welch algorithm to modify the starting HMM (λ) and to enhance the latest lecture path sequence also known as observed sequences as shown in Figure 4.3.

This algorithm comprised of forward variable (α) and backward variable (β). The probability of observation sequence of lecture material within time t and hidden state S_i at time t using model $\lambda = (A, B, \pi)$ is represented by forward variable.

$\alpha_t(i) = P(O_1, O_2, O_3......O_t, q_t = L_i, \lambda)$ ------------ (4.1)

$\beta_t(i) = P(O_{t+1}, O_{t+2}, O_{t+3}.....O_T, q_t = L_i, \lambda)$ ---------- (4.2)

The probability of being in hidden state L_i at time t and making a transition to state L_j at time t+1 given observation sequence $O = O_1,O_2,O_3...O_T$ using model $\lambda = (A,B,\pi)$.

$\xi_t(i,j) = P(q_t = L_i, q_{t+1} = L_j|O_1,O_2,...O_T, \lambda)$ --------- (4.3)

The probability of being in state L_i at time t given the observation sequence $O=O_1, O_2,...O_T$ and model $\lambda =(A, B, \pi)$.

$\gamma_t(i) = P(q_t = L_i|O_1, O_2, O_3 ....O_T, \lambda)$ ---------- (4.4)

As per Baum Welch algorithm [5], the starting and intermediate phase can be generalized in 4 steps.

1. For each student a HMM $\lambda = (A, B, \pi)$ is initialized.
2. Calculate $\alpha_t(i)$, $\beta_t(i)$, $\xi_t(i,j)$, $\gamma_t(i)$, t = 1....T, i=0,1,2...N-1, j = 0,1,...N-1.
3. Adjust $\lambda = (A, B, \pi)$.
4. If $P(O|\lambda)$ increases go to 2.

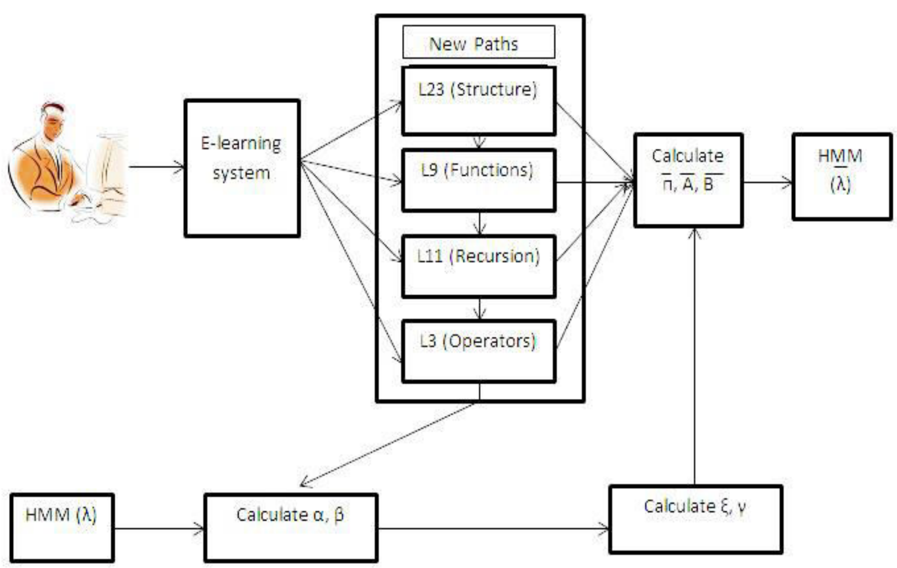


Figure 4.3 Intermediate Phase

In the last phase, probability $\alpha_t(i)$ of each lecture content was denoted as states for programming course, which was computed by forward algorithm as shown in Figure 4.4. After computation, maximum value was used to select the next future action or lecture content to be visited by students.

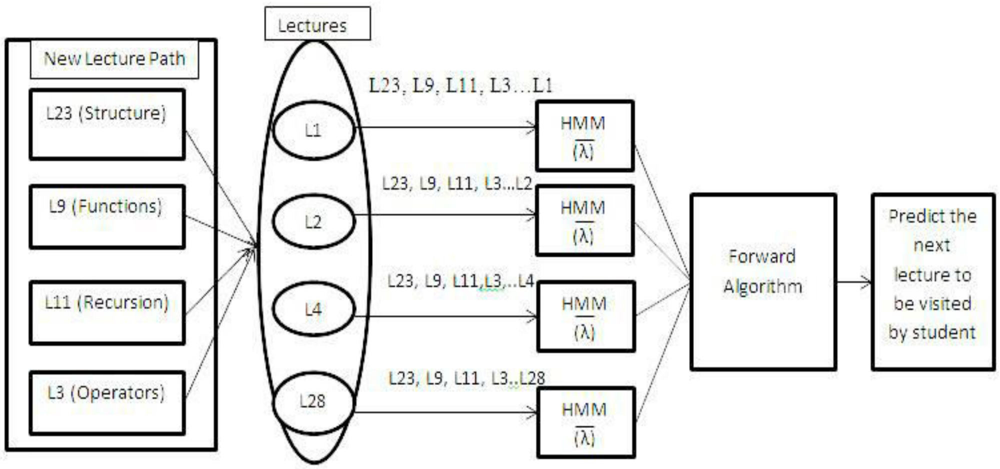


Figure 4.4 Final Phase

Forward Algorithm:

1. Set λ =(A, B, п) with random initial condition .
2. Set LTH=1 where LTH is the length of the observations or lecture path.
3. Increment LTH by 1. C=0 is the current iteration.
4. If (LTH<H) where H is the earlier details of count of lectures used for course then

   Set H=LTH

   Else

   Set LTH =H
5. The HMM model based on Baum Welch algorithm λ = (A, B, п) is modified on the basis of previous observations or lecture paths probability $O_{LTH-H+1}$, $O_{LTH-H+2}$, $O_{LTH-H+3}$…..O_{LTH}.

5.1 Calculate the forward variable α recursively.

$$\alpha_{LTH-H+1}(i) = \frac{\pi_k.b_k(O_{LTH-H+1})}{\sum_{i=0}^{N-1} \pi.\, b_i(O_{LTH-H+1})} \quad \text{------------------- (4.5)}$$

Where i = 0, 1, 2…N-1 and $\alpha_{LTH-H+1}(i)$ is the probability of observation ($O_{LTH-H+1}$) and hidden state L_k.

$$\alpha_t(j) = \frac{\sum_{i=0}^{N-1} \alpha_{t-1.} a_{ij} b_j(O_t)}{\sum_{j=0}^{N-1}\sum_{i=0}^{N-1} \alpha_{t-1}(i).\, a_{ij}.\, b_j\ (O_t)} \quad \text{------------------ (4.6)}$$

LTH = LTH-H+2, LTH-H+1,….,LTH, J=0,1,2…N-1, where $\alpha_t(j)$ is the probability of partial lecture paths until time t ($O_{LTH-H+1}$…..O_{LTH}) and hidden state L_j at time t.

$$\alpha_T(j) = P(O_{LTH-H+1}, O_{LTH-H+2},\ldots,O_{LTH}, q_{LTH} = L_j \mid \lambda) \quad \text{----------------- (4.7)}$$

The sum of forward variables $\alpha_T(j)$ gives the probability of observed sequence.

$$P(O_{LTH-H+1}, O_{LTH-H+2},\ldots,O_{LTH} \mid \lambda) = \sum_{j=0}^{N-1} \alpha_{LTH}(j) \quad \text{------------------ (4.8)}$$

5.2 Calculate the backward variable β recursively.

$$\beta_{LTH}(i) = \frac{1}{\sum_{j=0}^{N-1}\sum_{i=0}^{N-1} \alpha_{LTH-1}(i).a_{ij}.b_j(O_{LTH})} \quad \text{--------------------- (4.9)}$$

$$\beta_{LTH}(i) = \frac{\sum_{j=0}^{N-1} a_{ij}\ .\, b_j(O_{t+1}).\, \beta_{t+1}(j)}{\sum_{j=0}^{N-1}\sum_{i=0}^{N-1} a_{ij}.\, b_j(O_{t+1}).\, \beta_{t+1}(j)} \quad \text{--------------------- (4.10)}$$

Where, t= LTH-1, LTH-H+1, and i=0, 1, 2….N-1

5.3 Calculate ξ

$$\xi_t(i,j) = \frac{\alpha_t(i).\, a_{ij}.\, b(O_{t+1})\beta_{t+1}(j)}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \alpha_t(i).\, a_{ij}.\, b_j(O_{t+1})\beta_{t+1}(j)} \quad \text{-------------------- (4.11)}$$

t = LTH-H+1,…,LTH-1, i=0,1,2…N-1.

Where $\xi_t(i,j)$ is the probability of being in hidden state L_i at time t and making a transition to state L_j at time t and making a transition to L_j at t+1, with observation sequence $O_{LTH-H+1}$, $O_{LTH-H+2}$,….O_T.

5.4 Calculate γ

$\gamma_{LTH}(i) = \sum_{j=0}^{N-1} \xi_t(i,j)$ ---------------------------- (4.12)

t = LTH-H+1,…, LTH-1, i=0…N-1.

$\gamma_{LTH}(i)$ is the probability of being in state L_i at time t given sequence $O_{LTH-H+1}$, $O_{LTH-H+2}$…,O_{LTH}.

5.5 Adjust π

$\pi_i = \gamma_{LTH-H+1}(i)$

π_i represents the expected number of times the hidden state is L_i at the initial time t=LTH-H+1

5.6 Adjust A

$$a_{ijnew} = \frac{\sum_{t=LTH-H+1}^{LTH-1} \xi_t(i,j)}{\sum_{t=LTH-H+1}^{LTH-1} \gamma_t(i)} \quad \text{------------------------------- (4.13)}$$

5.7 Adjust B

$$b_j(k)_{new} = \frac{\sum_{t=LTH-H+1}^{LTH-1} 1_{yt=vk}\gamma_t(j)}{\sum_{LTH-H+1}^{LTH-1} \gamma_t(j)} \quad \text{--------------------------- (4.14)}$$

Here $1_{yt=vk}$ is an indicator function.

5.8 Increment c.

5.9 If $P(O_{LTH-H+1}\text{…..}O_{LTH} \mid \lambda_{new}) > P(O_{LTH-H+1}\text{…..}O_{LTH} \mid \lambda)$ then go to 5.

6. The next observation symbol or lecture path O_{LTH+1} can be predicted at time LTH with the help of adjusted model $\lambda_{new} = (A_{new}, B_{new}, \pi_{new})$.

6.1 Opt unobserved state L_i at time LTH, i=0, 1, 2…N-1, maximize $\alpha_{LTH}(i)$.

6.2 Opt next unobserved state L_j at time LTH+1 j=0, 1, 2…N-1, maximize a_{ijnew}.

6.3 Identify V_k next lecture at time LTH+1, k=0,…., M-1, maximize $b_j(k)_{new}$.

7. If procedure maintained then LTH=LTH+1 and go to step 4.
8. End.

4.3 Implementation

The web-based e-learning system identified the next lecture path or sequence to be visited by certain students based on their preference and skills. We have developed our e-learning system in Java language. The main entities used in our system are: students and faculty which are implemented as JSP class. They communicate each other by means of JSP MySQL database using the Apache web server.

Every lecture topics present in course curriculum of C programming is represented by letter L followed by a number, e.g. the lecture topic "Structure" is coded by L23. Lecture coding is not sequential, it is random. It can be interchangeable i.e. L15 can represent string also. The entire lecture topics covered in course module is shown in Table 4.1.

Table 4.1 Lecture topics of C Programming

Lecture number	Lecture Topics/paths/Concept	Lecture number	Lecture Topics/paths/Concept
L1	Identifiers and Keywords	L15	Array application
L2	Data types	L16	String
L3	Operators	L17	Manipulation of string
L4	Control transfer statements	L18	Pointers
L5	For, While, do-while	L19	Operation on pointers
L6	Formatted and Unformatted functions	L20	Passing Pointer to functions
L7	Type Conversion	L21	Array of pointers
L8	Type Modifiers	L22	DMA
L9	Functions	L23	Structures

L10	Parameters Passing Techniques	L24	Nested Structures
L11	Recursion	L25	Union
L12	Storage class	L26	File handling modes
L13	Arrays and types	L27	File handling operations
L14	Passing Array to function	L28	Macros

To determine the next lecture path or topic sequence visited by students, proper sequence was given with help of browsing option or by directly pasting in text field as shown in Figure 4.5 In the sequence we have given two options for prediction: prediction of a single lecture topic or multiple lecture topic in succession. In the system the user has option to select the sequence related to single or multiple concepts. Single concept referred that the topic was individual and not associated with any other major topics like array is related to function or structures. Multiple concepts refer that the topic is associated with multiple major topics like array with function or structure.

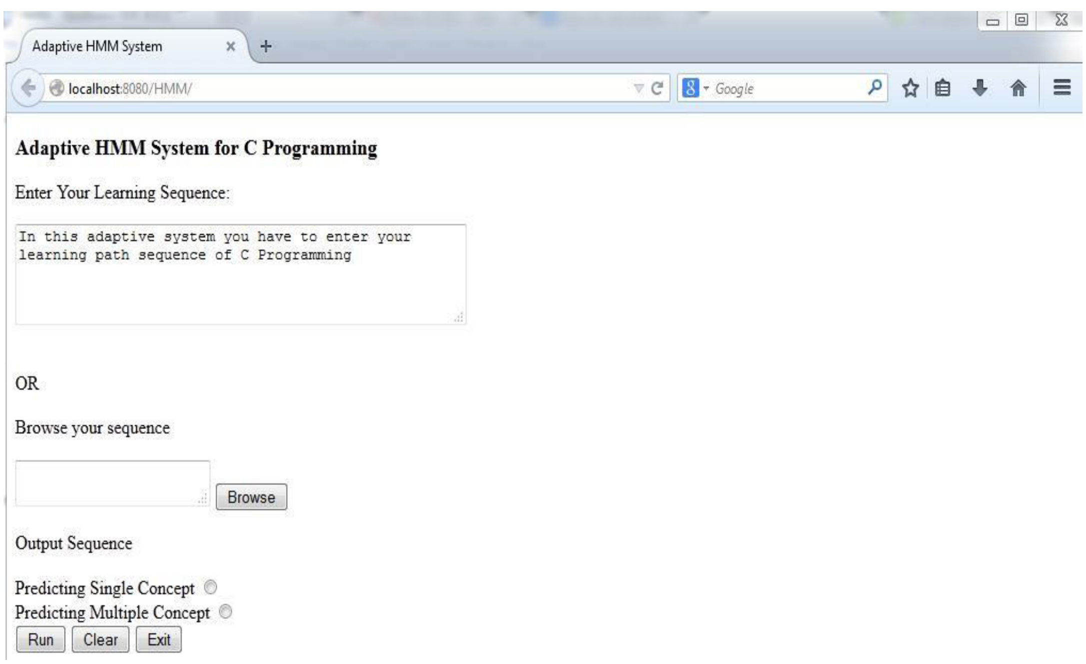


Figure 4.5 Adaptive HMM system

In this system, we have provided faculty module as shown in Figure 4.6 through which they have monitored student progress and helped learners in making suitable decisions based on their requirement. On the demand of students, the faculty has authority to deliver and instruct the exact learning material i.e. they can alter the learning material content and also changes the sequence of list initiated by web-based learning system.

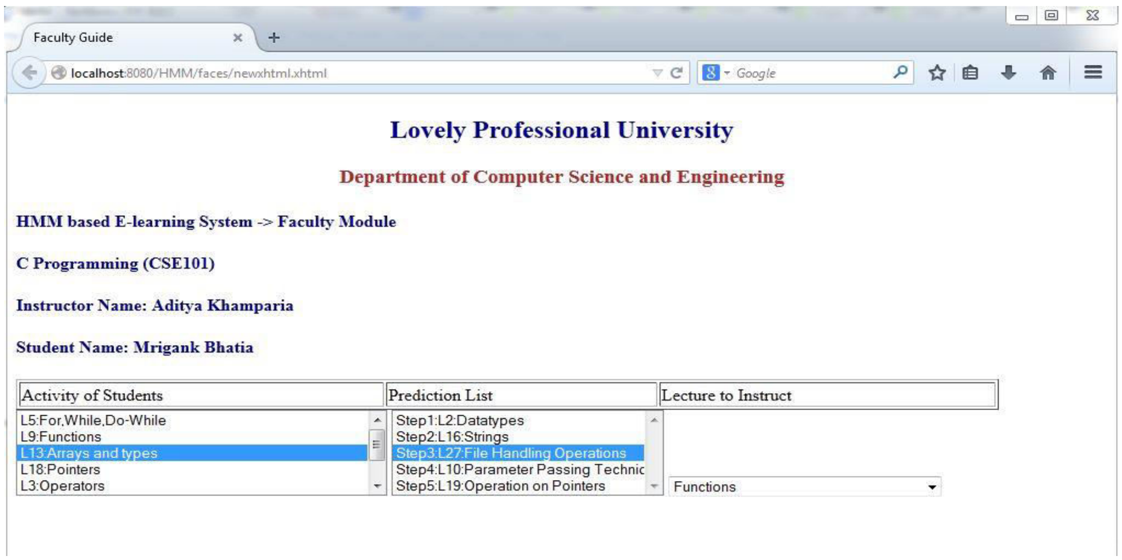


Figure 4.6 Faculty module

In order to provide suggestion to students based on lecture path they followed, a sequence with suggestions as shown in Figure 4.7 is presented to them where they want to know where to go next or which topic to be followed. Sequence has been provided to student based on their previous knowledge, skills and ability. Sequence based on navigational view was used to examine prediction modules i.e. short and long sequence of students. These single sequence or lecture paths were treated as training data for HMM predictor and multiple sequences were treated as testing data. For example student1 has lecture topic to be followed in sequence like L1 (Identifiers and Keywords), L2 (Data types), L3 (Operators), L18 (Pointers), L19 (Operation on pointers), L20 (Passing pointer to functions), L21 (Array of pointers), whereas for student2 it can be L18 (Pointers), L19 (Operation on pointers), L1 (Identifiers and keywords), L3 (Operators), L2 (Data types), L21 (Array of pointers), L20 (Passing pointer to functions). Student3 has navigation sequence for lecture topic it can be L1 (Identifiers and keywords), L19 (Operation on pointers), L20 (Passing pointer to functions) L21 (Array of pointers), L2 (Data types), L3 (Operators), L18 (Pointers).

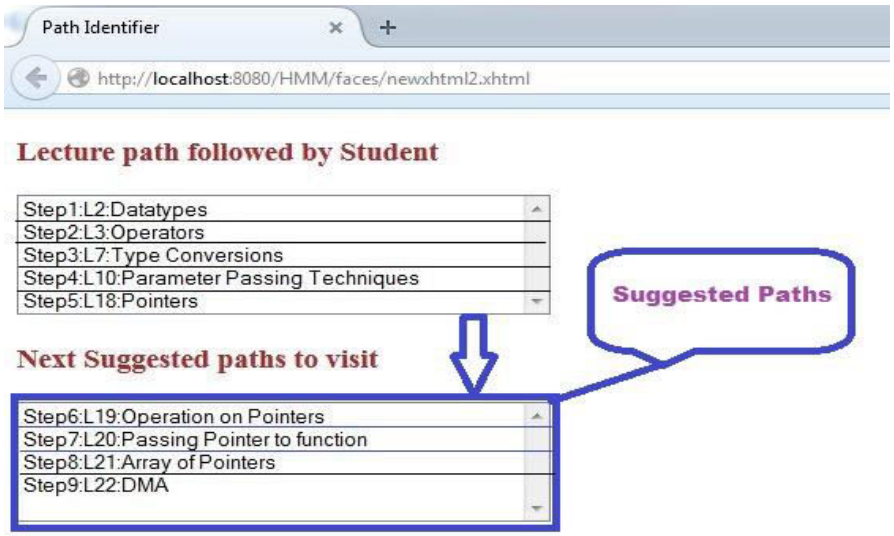


Figure 4.7 Sequence Path Suggestions

We have developed an HMM model for each learner with movements to individual other lecture path or topics. Individual node arc in HMM prototype is a lecture topic and movement among each nodal arc denotes the probability of learner movement through those lecture topics. All the lecture topics of programming course were represented as states. As shown in Figure 4.8 only partial HMM has been taken into consideration in which navigation has been made between different lecture topics.

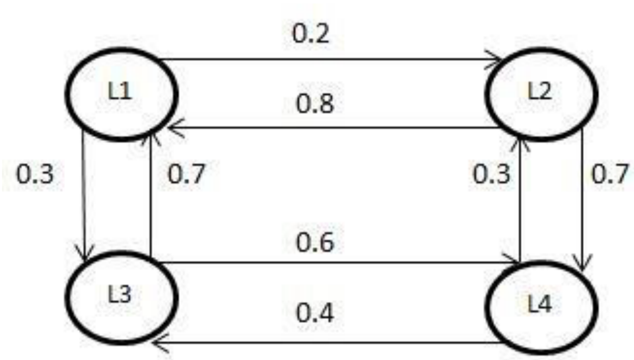


Figure 4.8 Partial HMM

4.4 System Evaluation

To obtain some feedback about our adaptive web-based e-learning system, we have demonstrated effectiveness of our HMM model through several experiments using C programming course taught in university. In this section we have presented the exercise/quizzes module selected for students (as shown in Figure 4.9) and gave feedback to them. A questionnaire has been prepared and distributed to students registered for C programming course in adaptive system. Two groups of 25 students each have been randomly selected to test the system. First group of 25 students have used offline paper exercise/quiz and second group have used our adaptive e-learning system. After result analysis or comparison it has been observed that both groups obtain approximately similar results. After taking the quiz, all the students had to fill in questionnaire with general questions regarding C programming and based on assessment methods.

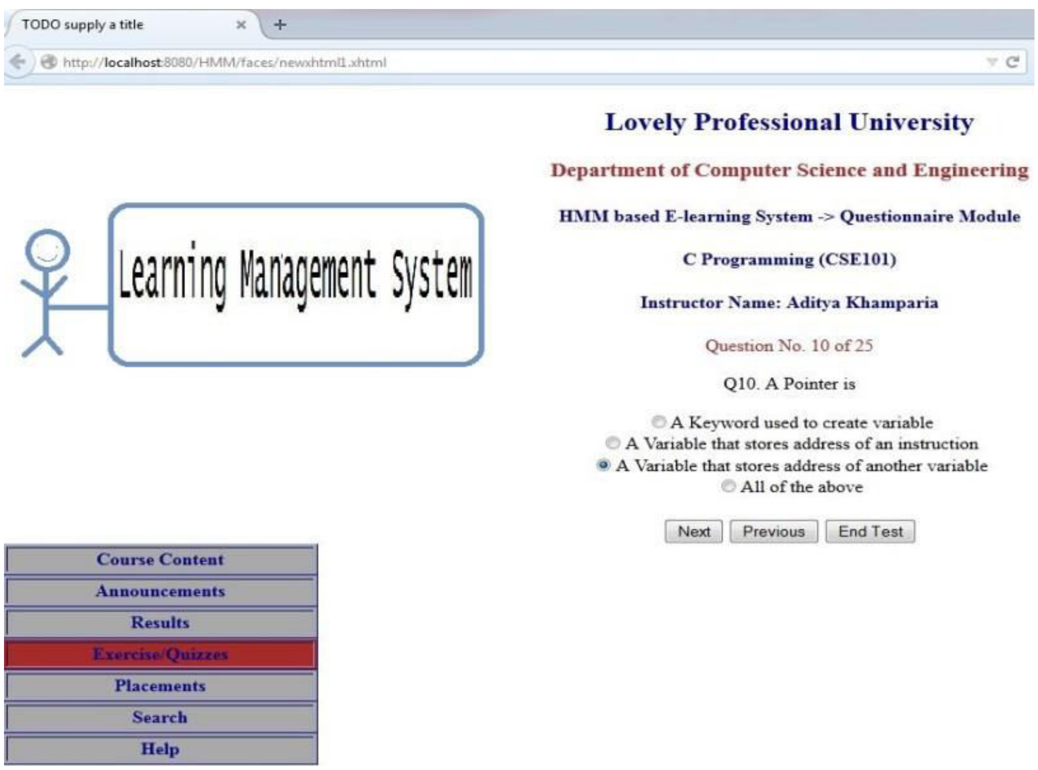


Figure 4.9 Exercise/Quiz Module

After getting response it has been observed that student who used the web-based e-learning system obtained their marks immediately after submitting response to server. Student who had given offline quiz they received the results the day after exam. Based on result analysis, most of the students are interested to know their grade details immediately after exam which shows they trust more a computer-based evaluation system rather than conventional methods.

To compare our proposed approach, we have designed a Multilayer perceptron network to predict the student actions and their progress in programming in coming months. Students actions were treated as the input of network. There were total 4 inputs: enrollment of student to programming course, decision of lecture topics, participation in exercise/quiz assessments, and interaction with faculty while asking questions, suggestions and discussion in class. The network has one output i.e. rate of improvement in student actions in coming time. The proposed model has 3 layers as 5-20-1 (input-hidden-output). It has been tested with record of 50 students data and evaluated with 25 data and performance rate achieved was 78.15 compared to HMM i.e. 80.23 which show that our HMM based approach was more effective in terms of performance.

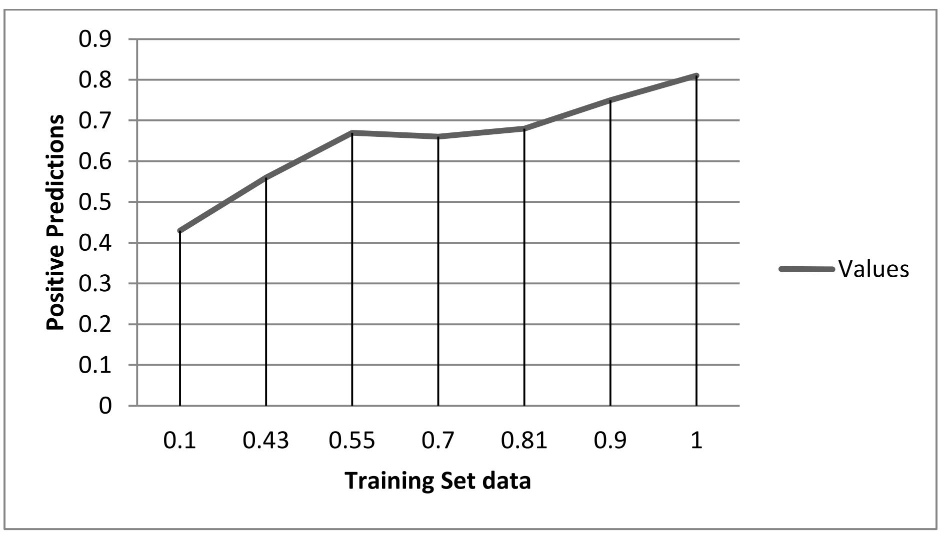


Figure 4.10 Test results

As shown in Figure 4.10 the percentage of positive predictions reaches up to 80% using 100% of training set which shows the number of correctly predicted concepts based on student actions.

4.5 Conclusions

As shown in the proposed chapter, data was collected from adaptive e-learning system and action of each student has been gathered according to every lecture topic which they visited based on history of concepts. We have discussed how HMM along with Baum-Welch algorithm has been used to predict the student future behavior and navigation actions within an e-learning system.

On the basis of result achieved, prediction percent of student actions equals to 80.23. To compare proposed approach, Multilayer perceptron neural network model was designed whose accuracy rate equals to 78.15. It shows that our method has acceptable performance and can be used as good tool for predicting future action of students to visit next lecture path or topics in C programming.

Chapter 5

Enhancing Learner Performance through Psychological and Environmental Factors

5.1 Introduction

E-learning has grown rapidly along with educational technology to provide rapid, accurate and complex content to individual based on their needs and preferences. Various researchers worked on different e-learning problems related to different fields and applications. Adaptive learning enables online delivery of dynamic content to individual based on different level of knowledge basics, preferences, styles, motivations, course interest and acquired learning skills (Wang et al, 2011; Norwawi et al, 2009). Variety of researchers worked on content adaptation and delivery of precise content and concluded that learning capability of individual learner was not dependent only on their learning characteristics. Variety of other factors played an important role in improving significant growth of learning capability, these factors are Psychological (P) and Environmental (E) factors which enhance overall grooming of learner (Baker, 2008; Ainley et al, 2009; Hanrahan, 1998).

Multifarious researchers (Wang et al, 2011; Baker, 2008; Ainley et al, 2009; Hanrahan, 1998) demonstrated that psychological factors: isolation, depression, anxiety and environmental factors: stress and improper guidance not only degrades the overall performance of individual learners but also affect the personality and individual growth of learners, as of now researchers have not considered these investigated parameters into consideration for research-based study.

There are mainly two types of important factors which we have considered in this study as positive and negative. The overall performance of learner and intended capability is enhanced by positive factors whereas negative diminished the learning performance of individual. If these complimentary or negative factors were not identified and diagnosed at early stages then it affects overall learning capability of learner. If sufficient amount of complimentary positive factors is provided then impact of negative factors get mitigated early at initial stages so that learning performance of learner could be improved.

Thus, in stated work we have deployed Hidden Markov Model (HMM) to predict the grade of learner on basis of their Psychological and Environmental factors and it also provide information regarding amount of complimentary factors to be provided in lieu of negative factors to improve performance. The concern behind choosing HMM is that it only considers prior probabilities (uses generative approach) unlike Artificial Neural Network (ANN), Support Vector Machine (SVM) which strictly dependent on posterior governed probability distribution (discriminative approach). Our proposed described work focuses on following objectives:

1. Deployment of Hidden Markov Model for prediction of learner’s grade (performance).
2. Behavioral observation of Hidden Markov Model on different psychological and environmental factors.
3. Mapping of individual negative Psychological and Environmental factors with their complementary positive Psychological and Environmental factors which would reduce the impact and effect of negativity and vice-versa.

Different Psychological and Environmental considered in work is described in Section 5.2. Basic concepts on Hidden Markov Model and related concepts is presented in section 5.3. Different results obtained with proposed algorithm and obtained accuracy is discussed in section 5.4.

5.2 Psychological and Environmental Set

Psychological factors comprised of Positive (P) and Negative (N) factors as shown in Figure 1.

1. N is set of negative factors i.e. $N = \{X_i: X_i \text{ is a negative factor}\}$
2. P is set of positive factors i.e. $P = \{Y_i: Y_i \text{ is a positive factor}\}$
3. $P \cap N$: X: $<X_i, Y_i>$ where $X_i \in P$, $Y_i \in N$ and X_i is complimentary factor of Y_i

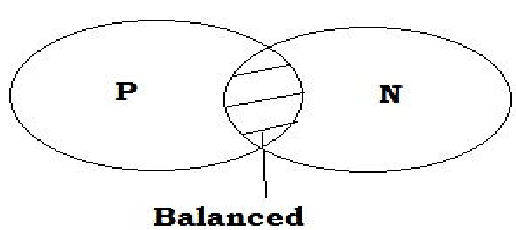


Figure 5.1 Psychological and Environmental Set (Positve & Negative factors)

The learning capability of student having all personality psychological factor lying in N (LC_N) is less than the learning capability of student lying in P∩N ($LC_{P\cap N}$).

The learning capability of ($LC_{P\cap N}$)is less than learning capability of the student in P (LC_P) as shown in equation 1.

$$LC_N < LC_{P\cap N} < LC_P \text{ ----------------------- } (1)$$

Therefore, from equation 1 it is clear that, If the student personality-psychological factor lying in N then by counseling (or by imparting any positive factor belongs to P) the performance of the student can reach to balanced level i.e. P∩N. In this region (P∩N) we only provide the positive factor which is complimentary to the negative factors with which students are suffering. Further when student reached at balanced level, we provide some more positive factors belongs to P to enhance the student performance.

Similarly, the Environmental factors also comprised of Positive (PE) and Negative (NE) factors as shown in Figure 5.1.

1. NE is set of negative factors i.e. NE = $\{X_k: X_k$ is a negative factor$\}$
2. PE is set of positive factors i.e. PE = $\{Y_k: Y_k$ is a positive factor$\}$
3. PE∩NE: X: $<X_k, Y_k>$ where $X_k \in$ PE, $Y_k \in$ NE and X_k is complimentary factor of Y_k,
   X_k is complimentary factor of Y_k if the negative effect of X_k attribute is neutralized or reduced by the positive effect of Y_k.

The learning capability of student having all environmental factor lying in NE (LC_{NE}) is less than the learning capability of student lying in PE∩NE ($LC_{PE\cap NE}$). The learning capability of ($LC_{PE\cap NE}$) is less than learning capability of the student in PE (LC_{PE}) as shown in equation 2.

$$LC_{NE} < LC_{PE\cap NE} < LC_{PE} \text{ ------------------------ } (2)$$

Therefore, from equation 2 it is clear that, if the student environmental factor lying in NE then by counseling (or by imparting any positive factor belongs to PE) the performance of the student can reach to balance level i.e. PE∩NE. In this region (PE∩NE) we only provide the positive factor which is complimentary to the negative factors with which students are suffering. Further when student reached at balanced level, we provide some more positive factors belong to PE to enhance the student performance.

The pairs of complimentary negative and positive attribute are shown in Table 5.1. The Positive Psychological factors are Connect/Gather(C/G), Pleasure/Comfort(P/C) and Trust (T) and the corresponding complementary negative Psychological factors are Isolation (I), Depression (D) and Anxiety (A) respectively (Khamparia and Pandey, 2016).

Similarly, the Positive Environmental factors are Proper Guidance (PG), Entertainment (E) and NEF are their complementary factors such as Improper Guidance (IG), Stress(S) respectively.

Table 5.1 Set of Complimentary Psychological and Environmental factors

<positive, negative>	Positive	Negative
<C/G, I>	C/G (Connect/Gather)	I (Isolation)
<P/C,D>	P/C (Pleasure/Comfort)	D (Depression)
<T, A>	T (Trust)	A(Anxiety)
<PG, IG>	PG(Proper Guidance)	IG (Improper Guidance)
<E, S>	E(Entertainment)	S(Stress)

5.3 Hidden Markov Model (HMM)

Hidden Markov Model is a statistical and stochastic markov model that speculates markov model along hidden states. It is represented by using dynamic Bayesian network. It expresses output dependent on the probability of the state rather than state itself; unlike markov model. Each output has probability associated with it. The transitions among states are governed by set of probabilities called transition probabilities (Mishra R., 2015; Severac et al., 2007). The states are undercover in this model; hence it is called Hidden Markov Model. HMM consists of three parameters as: HMM $\lambda = (A\ B\ \pi)$

Where A = Transition matrix, $a_{ij} = P$ (state S_j at t+1 | state q_i at t); B = N * M Emission matrix where N = number of states in model and M = number of observation symbols.

$b_j(k)$ = P(observation k at t| state q_j at t)

where A and B are row stochastic in the sense that sum of elements in a row is one and π = initial states.

HMM addresses three fundamental problems as:

- Given the model and observation sequences, $b_t = b_{01}\ b_{02}\ b_{03}\ldots\ldots b_{ON}$, the objective is to determine P(O|λ) efficiently i.e. the probability of the observation sequences for the given model λ.
- To determine the optimal sequences of states for given model, λ and observation sequences, O_i. This is solved efficiently by Viterbi algorithm.
- Estimation: It is to get the maximum P(O|λ) by estimating the parameters of model λ. This is solved by Baum-Welch Algorithm.

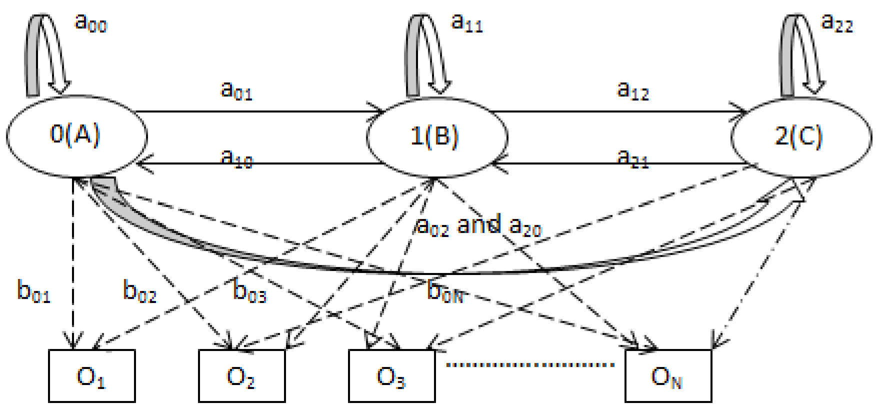


Figure 5.2 Proposed HMM Model

HMM Training

A. *Optimal value of state*

For a generic state sequence of length n, the state equation is given by (5.3.1):

$$X = (x_0\ x_1\ x_2\ x_3\ \ldots\ldots\ldots x_{n-1}\ x_n) \qquad (5.3.1)$$

And corresponding observation of length m is given by (5.3.2):

$O = (o_0\ o_1\ o_2\ o_3 \ldots\ldots. o_{m-1}\ o_m)$ (5.3.2)

The probability of state sequence X is given by

$P(X) = \pi\ x_0 b\ x_0(o_0) a\ x_{0,}\ x_1 b\ x_1\ (o_1) a\ x_1\ x_2\ b\ x_2(o_2)\ ax_2\ x_3\ b\ x_3(o_3) \ldots. ax_{n-1}\ x_{n-2}\ bx_n(o_n)$ (5.3.3)

For three states and five observations, we have A as 3*3 and B_1(positive) as 3*5 matrix and B_2 (negative) as 3*5 matrix respectively. The initial state is a vector 1*3. The matrix A, B1, B2 and initial state vector is represented as:

A =

	A	**B**	**C**
A	0.6	0.3	0.1
B	0.5	0.3	0.2
C	0.5	0.4	0.1

B_1 =

	C	**P**	**T**	**PG**	**E**
A	0.1	0.2	0.3	0.1	0.3
B	0.2	0.1	0.3	0.2	0.2
C	0.3	0.1	0.1	0.3	0.3
B_2=	I	D	A	IG	S
A	0.2	0.2	0.2	0.3	0.1
B	0.2	0.3	0.2	0.1	0.2
C	0.2	0.2	0.3	0.2	0.1

$\pi_0 = [0.4\ 0.3\ 0.3]$

Table 5.2 States Computation

Logical Combination	Product of states	Logical Combination	Product of states	Logical Combination	Product of states	Logical Combination	Product of states	Logical Combination	Product of states
AAAAA	0.000012441	ABCBA	0.000003456	BABCA	0.00000162	BCBAA	0.000000864	CBABA	0.00000144
AAAAB	0.00000622	ABCBB	0.000002073	BABCB	0.000001296	BCBAB	0.000000432	CBABB	0.000000864
AAAAC	0.000000691	ABCBC	0.00000046	BABCC	0.000000108	BCBAC	0.000000048	CBABC	0.000000192
AAABA	**0.000010368**	ABCCA	0.000001296	BACAA	0.00000081	BCBBA	0.000000864	CBACA	0.00000072
AAABB	0.00000622	ABCCB	0.000001036	BACAB	0.000000405	BCBBB	0.000000518	CBACB	0.000000576
AAABC	0.000001382	ABCCC	0.000000086	BACAC	0.000000045	BCBBC	0.000000115	CBACC	0.000000048
AAACA	0.000005184	ACAAA	0.000001728	BACBA	0.00000108	BCBCA	0.000000864	CBBAA	0.000000864
AAACB	0.000004147	ACAAB	0.000000864	BACBB	0.000000648	BCBCB	0.000000691	CBBAB	0.000000432
AAACC	0.000000345	ACAAC	9.6E-08	BACBC	0.000000144	BCBCC	0.000000057	CBBAC	0.000000048
AABAA	0.000005184	ACABA	0.00000144	BACCA	0.000000405	BCCAA	0.000000324	CBBBA	0.000000864
AABAB	0.000002592	ACABB	0.000000864	BACCB	0.000000324	BCCAB	0.000000162	CBBBB	0.000000518
AABAC	0.000000288	ACABC	0.000000192	BACCC	0.000000027	BCCAC	0.000000018	CBBBC	0.000000115
AABBA	0.000005184	ACACA	0.00000072	BBAAA	0.000001944	BCCBA	0.000000432	CBBCA	0.000000864
AABBB	0.00000311	ACACB	0.000000576	BBAAB	0.000000972	BCCBB	0.000000259	CBBCB	0.000000691
AABBC	0.000000691	ACACC	0.000000048	BBAAC	0.000000108	BCCBC	0.000000057	CBBCC	0.000000057
AABCA	0.000005184	ACBAA	0.000001152	BBABA	0.00000162	BCCCA	0.000000162	CBCAA	0.000000864
AABCB	0.000004147	ACBAB	0.000000576	BBABB	0.000000972	BCCCB	0.000000129	CBCAB	0.000000432
AABCC	0.000000345	ACBAC	6.4E-08	BBABC	0.000000216	BCCCC	0.00000001	CBCAC	0.000000048
AACAA	0.000002592	ACBBA	0.000001152	BBACA	0.00000081	CAAAA	0.000002592	CBCBA	0.000001152
AACAB	0.000001296	ACBBB	0.000000691	BBACB	0.000000648	CAAAB	0.000001296	CBCBB	0.000000691
AACAC	0.000000144	ACBBC	0.000000153	BBACC	0.000000054	CAAAC	0.000000144	CBCBC	0.000000153
AACBA	0.000003456	ACBCA	0.000001152	BBBAA	0.000000972	CAABA	0.00000216	CBCCA	0.000000432
AACBB	0.000002073	ACBCB	9.216E-07	BBBAB	0.000000486	CAABB	0.000001296	CBCCB	0.000000345
AACBC	0.00000046	ACBCC	7.68E-08	BBBAC	0.000000054	CAABC	0.000000288	CBCCC	0.000000028
AACCA	0.000001296	ACCAA	0.000000432	BBBBA	0.000000972	CAACA	0.00000108	CCAAA	0.000000432
AACCB	0.000001036	ACCAB	0.000000216	BBBBB	0.000000583	CAACB	0.000000864	CCAAB	0.000000216
AACCC	0.000000086	ACCAC	0.000000024	BBBBC	0.000000129	CAACC	0.000000072	CCAAC	0.000000024
ABAAA	0.000005184	ACCBA	0.000000576	BBBCA	0.000000972	CABAA	0.00000108	CCABA	0.00000036
ABAAB	0.000002592	ACCBB	0.000000345	BBBCB	0.000000777	CABAB	0.00000054	CCABB	0.000000216
ABAAC	0.000000288	ACCBC	7.68E-08	BBBCC	0.000000064	CABAC	0.00000006	CCABC	0.000000048
ABABA	0.00000432	ACCCA	0.000000216	BBCAA	0.000000972	CABBA	0.00000108	CCACA	0.00000018
ABABB	0.000002592	ACCCB	0.000000172	BBCAB	0.000000486	CABBB	0.000000648	CCACB	0.000000144
ABABC	0.000000576	ACCCC	0.000000014	BBCAC	0.000000054	CABBC	0.000000144	CCACC	0.000000012
ABACA	0.00000216	BAAAA	0.000003888	BBCBA	0.000001296	CABCA	0.00000108	CCBAA	0.000000288
ABACB	0.000001728	BAAAB	0.000001944	BBCBB	0.000000777	CABCB	0.000000864	CCBAB	0.000000144
ABACC	0.000000144	BAAAC	0.000000216	BBCBC	0.000000172	CABCC	0.000000072	CCBAC	0.000000016
ABBAA	0.000002592	BAABA	0.00000324	BBCCA	0.000000486	CACAA	0.00000054	CCBBA	0.000000288
ABBAB	0.000001296	BAABB	0.000001944	BBCCB	0.000000388	CACAB	0.00000027	CCBBB	0.000000172
ABBAC	0.000000144	BAABC	0.000000432	BBCCC	0.000000032	CACAC	0.00000003	CCBBC	0.000000038
ABBBA	0.000002592	BAACA	0.00000162	BCAAA	0.000001296	CACBA	0.00000072	CCBCA	0.000000288
ABBBB	0.000001555	BAACB	0.000001296	BCAAB	0.000000648	CACBB	0.000000432	CCBCB	0.00000023
ABBBC	0.000000345	BAACC	0.000000108	BCAAC	0.000000072	CACBC	9.6E-08	CCBCC	0.000000019
ABBCA	0.000002592	BABAA	0.00000162	BCABA	0.00000108	CACCA	0.00000027	CCCAA	0.000000108
ABBCB	0.000002073	BABAB	0.00000081	BCABB	0.000000648	CACCB	0.000000216	CCCAB	0.000000054
ABBCC	0.000000172	BABAC	0.00000009	BCABC	0.000000144	CACCC	0.000000018	CCCAC	0.000000006
ABCAA	0.000002592	BABBA	0.00000162	BCACA	0.00000054	CBAAA	0.000001728	CCCBA	0.000000144
ABCAB	0.000001296	BABBB	0.000000972	BCACB	0.000000432	CBAAB	0.000000864	CCCBB	8.64E-08
ABCAC	0.000000144	BABBC	0.000000216	BCACC	0.000000036	CBAAC	9.6E-08	CCCBC	0.000000019
CCCCA	0.000000054	CCCCB	0.000000043	CCCCC	0.000000003				

We have taken three states in the form of grades as A, B and C. Similarly, five observations [2 6 8 4 3] for different emission probabilities as 2 = pleasure, 3=Trust, 4 = Proper guidance, 8= Anxiety, and 6 = Isolation respectively that logically produces 243 combinations as shown in Table 5.2. We have calculated the probabilities of optimal states as shown in line of the different logical combinations.

B. Proposed Algorithm

```
1.  Start
2.  Read number of states, numstate from user.
3.  Read number of observations, numobs from user
4.  Read state symbols, vec[1,numstate]  from user.
5.  Read initial probability of states, p[1,numstate] from user
6.  for l=1 to numstate
7.      Read positive emission matrix, emis_pos[l,:] from the user for lth state
8.      Read negative emission matrix, emis_neg[l,:] from the user for lth state
9.   end for
10.  for l=1 to numstate
11.         Read transition matrix, trans[l,:] from user
12.  end for
13. Totalposs=numstate^numobs
14. D=totalposs/numstate
15. Create state combination table using following algo
16.   for k=1 to numobs
17.    q=1, z=1
18.       for l=1 to totalposs
19.              if(z<=d)
20.                     a(l,k)=vec(1,q);
21.                     z=z+1
22.                     if(z==d+1)
23.                          q=q+1
24.                           z=1
25.                      end if
26.                     if(q==(numstate+1))
27.                          q=1
28.                     end if
29.              end if
30.       end for
31.     d=d/numstate
32. end for
33. Read observation sequence, veco[1,numobs] from user
34. repeat  35 to   60     for all state combinations
35.         initial_bit_test=0
36.         previous_state=1
37.         product_of_state=1
38.              for k=1  to numobs
39.                     t=a(l,k)
```

```
40.                 Repeat 41 to 60 for all State Symbols
41.                 Read position of state symbol in vec matrix,pos
42.                   if( initial_bit_test ==0)
43.                          if(veco(1,k)<((numobs))+1)
44.
     product_of_state=product_of_state*(p(1,pos)*EMIS(pos,veco(1,k)));
45.                          else
46.                               hg=veco(1,k)-(numobs)
47.                              product_of_state= product_of_state * (p(1,pos)*((EMIS1(pos,hg))))
48.                         end if
49.                     initial_test=1
50.                    previous_state=pos
51.                 else
52.                   if(veco(1,k)<((numobs))+1)
53.
     product_of_state=product_of_state*(TRANS(prevstate,pos)*EMIS(pos,veco(1,k)))
54.                  else
55.                      hg=veco(1,k)-(numobs)
56.
     product_of_state=product_of_state*(TRANS(prevstate,pos)*((EMIS1(pos,hg))))
57.                  end if
58.                      previous_state=pos
59.              end if
60. end for
61. repeat 62 to 69 for all states
62.   for l = 1 to totalposs
63.    for s= 1 to numobs
64.       if(statecombination(l,s)==vec[1,1]
65.           sumofbitswise_of_state(i)[1,s]==product_of_state
66.      end if
67.   end for
68.  end for
69. i=1+1
70.  repeat 71 and 72 for all bits of observations
71. find maximum of ith bit from sumofbitswise_of_state of all states
72.   beststate[1,i]= state with maximum bit sum
73. search beststate among state combinations using any search technique
74.  find corresponding product of state
75. End
```

Computation of states

Here, as shown in Table 5.2 A, B and C represent different states in the form of grades which are obtained by student respectively. The numerical value in the even columns i.e. product of states corresponding to their respective logical combinations in odd column is calculated by (5.3.3). Such states computation has been done earlier by (Mishra R, 2015) in proposed work. For example, in Table 5.2, the various values in numerical form in the first row of columns 2, 4, 6, 8, 10 as 0.000012441, 0.000003456, 0.00000162, 0.000000864 and 0.00000144 respectively correspond to the logical combinations, given in the same row in the columns 1, 3, 5, 7, 9 as AAAAA, ABCBA, BABCA, BCBAA and CBABA.

Table 5.3 shows the sum of A (grades) states, where A is in the first, second, third, fourth and fifth places in Table 5.2. Similarly, the second row shows the sum of B in the increasing order of places in Table 5.2. From each of the column we select the highest value which is 0.0001461 in the first place in first column corresponding to observation (2) i.e. pleasure out of given observations. Similarly, for second observation (6) i.e. Isolation the highest value is 0.00013105 as shown in second column. The detailed description of Table 5.3 is given below.

Table 5.3 Sum of States

	1	2	3	4	5
A	**0.0001461**	**0.00013105**	**0.00011799**	0.000085686	**0.00014029**
B	0.000054854	0.000077539	0.000075354	**0.00009179**	0.000085113
C	0.000036717	0.000029082	0.000044323	0.000060194	0.000012271

5.4 Result and Discussion

The order of probability of occurrence of a particular state depends on the observation of a particular set of emissions in a time sequence. In our case, the observation [2 6 8 4 3] is for the time sequence, starting from t_0 as present and t_1, t_2, t_3, t_4, t_5 for the consecutive past times, corresponding to observation 2 6 8 4 3 respectively. Table 5.3 is obtained by the calculation of the sum of probabilities, when the states A, B and C are in the first, second, third, fourth and fifth positions in the 243 logical combinations of states as shown in Table 5.2. The interpretation of Table 5.3 is as follows:

For the 2 as P (Pleasure) observation at time t_1 the value of state P(A) is 0.0001461, for state B it is 0.000054854 and for the state C it is 0.000036717 in the first column of Table 5.3. It means that state A is more active than the state B and C. Similarly, it is observed that for the observations at other consecutive past time sequences i.e. Working at time t_2 for 6 as I (Isolation), P(A):0.00013105 > P(B):0.000077539>P(C):0.000029082; for 8 as A (Anxiety) P(A):0.00011799 > P(B):0.000075354 > P(C):0.000044323; P(B):0.00009179 > P(A):0.000085686 > P(C):0.000060194 for observation instance 4 as PG (Proper guidance); for instance 3 as T (Trust) P(A):0.00014029 > P(B):0.000085113 > P (C): 0.000012271.

We obtained the optimal sequence of states AAABA for the observation sequence [2 6 8 4 3] i.e. P I A PG T taking into account the greater value from each column of Table 5.3.

The computation of product of states for the observation sequence (2 6 8 4 3) and the states logical combination AAABA is done in following steps:

Step 1: The initial value for state A is taken as πx_0 is 0.4 and bx_0 (o_0) and its value from the emission table B_1 in the first row for A is P (0.2) and their product is 0.08.

Step 2: Write the transition from state A to A from the state transition matrix A which is 0.6 and the value of observation variable from the matrix B_2 as I (0.2) and their product is 0.12.

Step 3: Repeat the step 2 to obtain the transitions A-A, A-B and B-A as 0.6, 0.3 and 0.5 respectively to obtain the product of logical combination of states A A A B A as 0.000010368 as shown in Table 5.2.

5.5 Related Works

Varity of machine learning techniques which follows hidden states methodology like HMM (Mishra R, 2015), Bayesian networks, etc. used for predicating different real-world applications due to different theoretical basis and formulate strong mathematical structure for optimizing several applications. It is mostly adopted in voice and character identification, virtual learning systems, advanced bioinformatics system. The conducted related works have been classified or structured into different categories as MLP and soft computing, Virtual and augmented e-learning systems, semantic web and related technologies, CBR and student's characteristics.

5.5.1 Intelligent computing technique in E-learning:

The technique which understands the structure of system with help of given useful information on basis of raw data is known as Machine learning (Witten et al. 2011). Advanced supervised learning techniques like Hidden Markov, Association mining, ANN, Adaptive web-based learning and Bayesian networks have been used to achieve different objectives like to personalize the material to be delivered and suggest it to correct learner on basis of its needs (Baylari and Montazer 2009) for correct identification of learning styles (Ozpolat and Akar 2009). (Chen et al, 2005) used HMM in Internet enabled English questionnaire system for delivering adaptive content to learner based on their categorization, needs and preferences. Weighted Markov model has been proposed by (Huang et al. 2008) for next state prediction and consistency of next learner path has also been preserved. (Hsia et al., 2006) removes the choices using data mining and predict the future choice of internet enabled educational learning at University in Taiwan. (Norwawi et al, 2009) adopted Visual, Aural, Read and Kinesthetic kind of style to improve the learning programming skills with help of various machine learning techniques like Clustering and Mining analysis. Individual stocks price retrieval, identification, growth in sector and business stocks results which adopted HMM approaches were analyzed by (Hassan and Nath, 2005). (Cooper et al, 2007) modeled different exercises related to graphics, animations to organize the content effectively based on learner's choices. (Birney, 2001) adopted hidden markov model and perform prediction and coding of gene identification for DNA structures as different sequence of various animals and plants. (Huang and Chen, 2007) adopted genetic, CBR and adaptive mining techniques which test learning requirements of an individual and generates personalized learning system.

Such type of adaptive machine learning based algorithms identifies suitable learning style for AEs (Castro et al. 2007; Lo and Shu 2005; García et al. 2007), learners experience has been utilized for data access and storage (Romero et al. 2013; Kujala et al. 2010; Chrysafiadi and Virvou 2012) and identified learning content easily (Yang and Wu 2009).

5.5.2 Adaptive web-based e-learning systems

(Homsi et al, 2010) determined Markov Model as a software for identification of next upcoming topics learned by different users in an internet enabled English language system for teaching of other native language. (Hsieh et al, 2010) developed e-learning based adaptive system which generates and recommend several learning materials to learner's according to their preference and needs. (Tseng et al, 2008) developed an expertise web based system which has distinguished framework that segments and converts learning content into modular learning units.

5.5.3 Learner Characteristics

The performance of individual learners could be obtained by considering their prolific features and steps to retrieve course from courseware. (Yang et al. 2008) considered multi criteria based personalized system which considers various characteristics of learner with aid of Silverman style of learning and cognitive abilities. (Seters et al. 2012) predicted the expected learning path generated and visited by them by considering their motivation level, earlier subject interest, preferences and strategies. (Wang and Liao, 2011) discussed English language teaching and learning system which focuses on different learner's characteristics like anxiety level, motivation level, personality level and gender.

5.5.4 Ontology and Semantics

Any specific domain knowledge can be represented in terms of class is modeled by ontology. Ontology is a process of specifying the meaning of concepts (Gruber, 1993). By involving correct procedures, AEs tried to build instructions available for content construction in e-learning scenarios (Jia et al. 2011). Different ontology technique adopted by (Chu et al. 2011b) to develop learner skills with help of retrieval, searching and integration techniques.

Learning concepts conceptualization has been combined with ontology for usage in semantic web-based learning content (Aroyo et al. 2004) and diagnosing problem of learner (Shafrir and Etkind, 2006).

5.5.5 CBR based learning

(Gilbert and Han, 1999) developed the system for enrollment of learner to independent groups on the basis of their previous learning skills, interest and experience using case-based reasoning system and provide them adaptive contents. (Pandey et al. 2014) proposed case-based reasoning system which infers programming ability of user by considering their features and provide materials to them based on their learning need, knowledge level and preferences.

5.6 Conclusions

In this chapter, we have deployed the Hidden Markov Model to enhance and improve the learner's grades based on consideration of psychological and environmental factors which played major role in improving learner performance. For smooth training of HMM, we have initialized various parameters like transition probabilities (A), observation probabilities (B_1 and B_2) and initial state distribution (π). For improving feasibility, performance and verification of implemented HMM model the different logical combinations of states being considered in which best state would validate the suitability of particular observation sequence. This demonstrated that learning graph of individuals could be effectively improved by deploying Hidden Markov Model in deploying e-learning system. With the help of HMM model the total number of computations is reduced at great extent and with help of it we predict the grade at intermediatary stage also which is not possible by any other prediction models.

Chapter 6

Petri Net Based Threat Modeling Framework for E-Learning System

6.1 Introduction

In today's era, varieties of e-learning systems have security related problems (Hecker., 2008) but it is important to address such concerns related to security in initial stages of development cycle of related security systems (Jalal et al. 2008). Different types of e-learning systems are formally designed on basis of formal techniques which provides modeling of threats only in requirement phase but not in analysis and testing phase of the existing systems. Such formal techniques were not guaranteed that it removes design vulnerabilities of the system very easily and effectively.

A petri net is one of mathematical modeling tool used for the detailed description of discrete driven distributed and time event systems. It could be represented as directed graph where transitions were represented by arcs and places were depicted by graph nodes (Murata., 1989). The graphical model used stepwise process of refinement which include different iterations, choices and executions of different node driven systems. Mathematical case driven modeling was used by Petri nets to perform analysis of heterogeneous processes. Different categories of petri nets were used to model system behaviour like colored petri nets (Houmb and Sallhammar 2012), timed petri nets and stochastic petri nets. Stochastic Petri Nets (SPNs) models distributed computing architectures and other software usages (Peterson, 1977).

Varieties of threats occurred in system were categorized according to standards of (STRIDE) like identification of spoofing, data tampering, repudiation, disclosure of information, denial of service and privilege of elevation has been considered (Howard, 2003).

The stated work is published in: Aditya Khamparia, Babita Pandey.: Threat driven modelling framework using petri nets for e-learning system. In: Springer Plus (SCI-E, Thomson Reuters) Vol. 5, issue 1, pp. 446-450, (2016).

Variety of new phases governed by threat-based modeling framework was added with stochastic petri nets and different aspects. Numerous benefits are provided by such threat driven model as 1) it become easier to identify threats available in different applications and understandable by researchers; 2) complex fault detection and identification at individual levels become easier which enhance the efficiency of system.

In this chapter, threat driven security framework which involved stochastic petri nets has been proposed to remove the design vulnerabilities in system. The completeness and soundness of Aspect oriented stochastic petri nets models could be measured by proposed modified threat driven framework (Dehlinger and Nalin, 2006). Varieties of threat modeling phases like assessment of risk, mitigation assessment, attenuation description were added to proposed modeling framework which enhance efficiency and accuracy of proposed model. The risk introduced in analysis phase measured by computing the occurrence of threats and their related impacts were determined in system. To measure the correctness of proposed work, we have measured the three behavioral properties of petri nets: boundness, reachability and liveness. Different mitigations effectiveness could be observed on the basis of calculations of security metrics, which enables different researchers of e-learning communities to compare various mitigation effectiveness.

The organization of the work as follows: Section 6.2 presents the definition of aspect oriented stochastic petri net model. Proposed modified threat modeling framework is described in section 6.3. The proposed methodology on security metric parameters and computation is shown in section 6.4. Section 6.5 described the vulnerabilities and their results based on severity used in security computation. Section 6.6 concerned with performance evaluation. In section 6.7 the related works and comparisons are presented. Finally, section 6.8 brings out the conclusion.

6.2 Aspect Oriented Stochastic Petri Net Model (AOSPN)

In this work aspect oriented stochastic petri net model is deployed. In AOSPN model, Aspects are denoted as units that modularize the cross-cutting concerns (Schauerhuber et al., 2006). The combination of different base driven modules and aspects formulate aspect-oriented program. The advice is inserted at point i.e. called join point. In the stochastic petri nets joint points are transitions and arcs. The join point is represented by different language constructs called point cut. Whether specified join point matches according to specified criteria or not is designated by point cut. Basically, it is of three types: transition, predicate and arc (DianXiang and Kendall, 2006). An introduction net allows the new members and aspects to modify the static program structure and join base modules.

A structure composed of SPNs is <P, D, I> where P is defined as construct of pointcuts, D is collection of advice nets and I is represented as introduction sets.

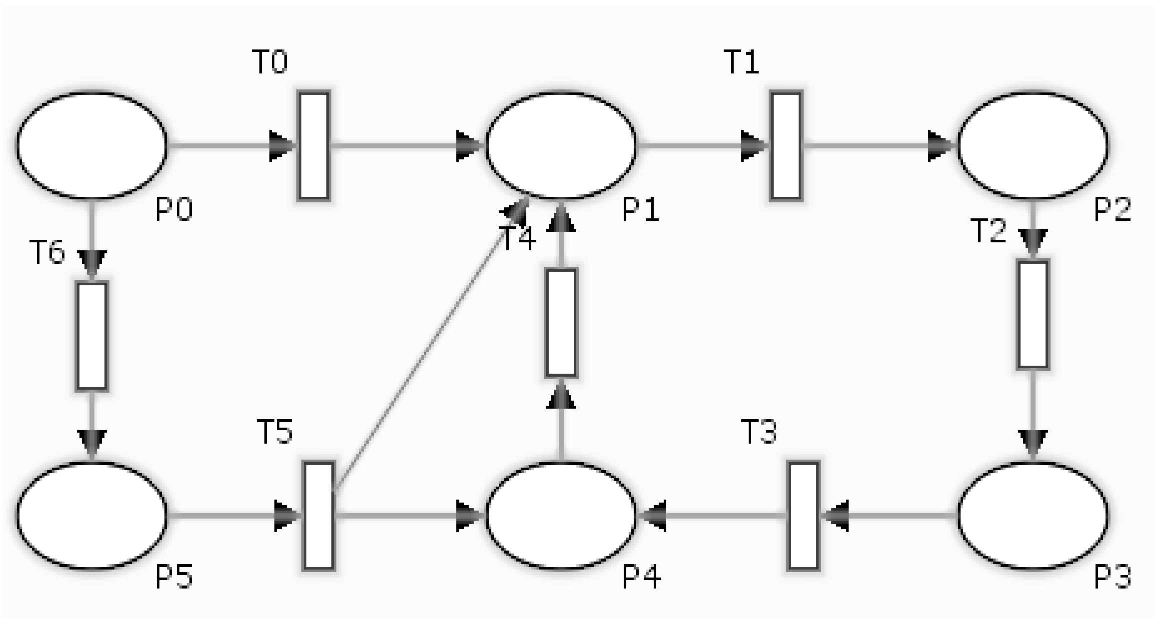
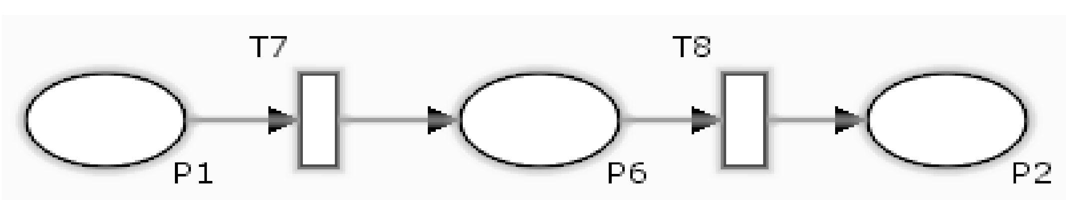


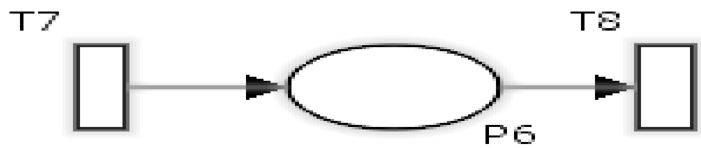
Figure 6.1 Stochastic petri net N1

Aspect Net

Pointcut tcut: N1.T1



(a) Advice tcut:



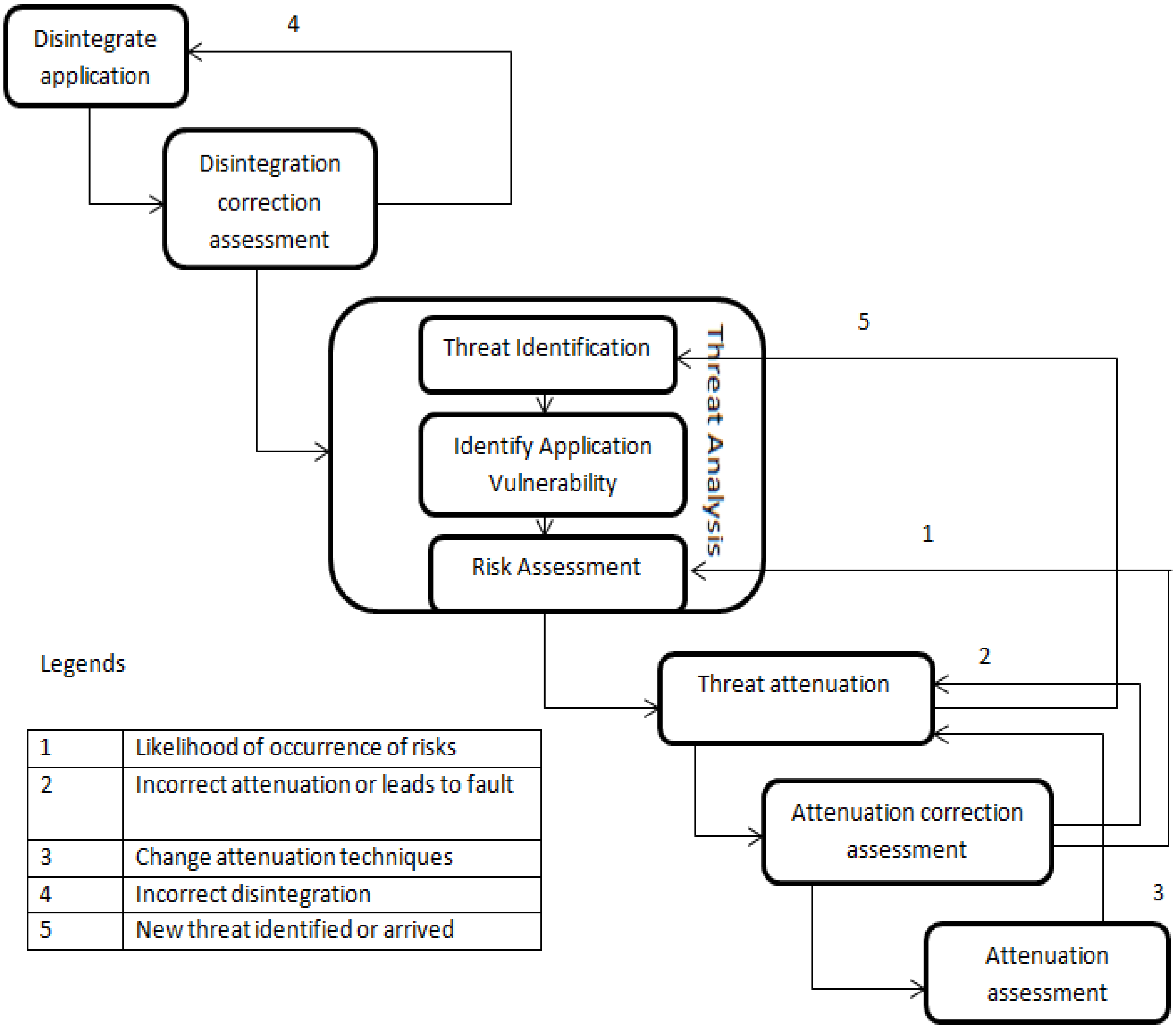
(b) Introduction net

Figure 6.2 An aspect model with Advice and Introduction net

Assuming that threat was occurred in SPN N1 in T1 transaction which is time bounded as shown in Figure 6.1. The pointcut as described in Figure 6.2 describes the threat place, how to weaved the mitigation would be specified by advice nets whereas the entire mitigation would be illustrated by introduction nets. In different aspects with different weaving ways, base driven net does not incorporate with stochastic petri nets. Stochastic driven petri nets could have weaved well with original base nets. Aspects applied to base net is not significant in order which rules applied.

Due to scarcity of data the challenges faced by system in net cannot tackled alone by AOSPN models and prediction of different future security attacks are still unknown. The identification of attackers behavior at such instant is very difficult to maintain. CVSS is used for identification of attacks, reports and information related to vulnerabilities. The advantage of CVSS is that the problem of addressing vulnerabilities could be handled easily in collaboration with product vendors. CVSS couldn't categorized attacks on different levels and also not provides model for estimating and prediction of risks at different levels. The operational level information about vulnerabilities could be easily provided by CVSS and leave rest of the information for vendors to add and describe their products which facilitates customers to purchase product according to their choice and evaluate them based on the targets they specified. It's always beneficial to involve usage of environmental metrics along with base and temporal metrics which are essential components in our approach to compute integrity, confidentiality and availability rather than productivity, reputation and privacy (Houmb and Franqueira, 2009).

6.3 Modified Threat Driven Modeling Framework



1	Likelihood of occurrence of risks
2	Incorrect attenuation or leads to fault
3	Change attenuation techniques
4	Incorrect disintegration
5	New threat identified or arrived

Figure 6.3 Threat driven modeling framework

The security in software driven e-learning systems has been provided by proposed threat driven modeling framework as shown in Figure 6.3. This proposed framework comprised of six steps which are Disintegrate application (decomposition), Disintegration correction assessment, Threat analysis (Threat identification, Identify Application vulnerability, and Risk assessment), Threat mitigation, Mitigation correction assessment and Mitigation assessment.

The proposed threat framework has variety of changes in comparison to traditional framework proposed by (Shrief et al. 2010). Initial steps on application decomposition, identification of threats and their mitigation is carried out from traditional threat framework of (Shrief et al. 2010) and (Howard, 2003), whereas other steps were synchronized with usage of SPNs (Murata 1989; Peterson 1977; Haas 2002; Wang et al. 2009).

- **Disintegrate application:** In this phase the modeling of different modules cold be done using stochastic petri nets on requirement of existing systems. Models those adopted Unified modeling language could be transformed to petri nets which are stochastic in nature. Then, petri nets utilized as deliverables for different software system functions based on requirement.
- **Disintegration correction assessment:** The behavioral aspects of stochastic petri nets would be tested which relied on different properties of nets like liveness, safeness, boundness and reachable ability of testing system. After changing the behavioral properties of petri nets if the system could reach to deadlock or starving phase then changes could be propagated by reversing the state to previous stable state.
- **Threat analysis:** The stated phase comprised of mainly three important steps as Threat identification, vulnerability identification of applications and assessment of risks at different level. Once decomposition phase done, identification and modeling of threats done with help of stochastic petri nets. Different kind of threats marked on petri nets as point cuts and categorized using STRIDE. Variety of vulnerabilities were detected for different e-learning related applications. These vulnerabilities are listed as: (authentication, authorization, input & data validation, configuration management, session management, auditing & logging etc.) for distinguished applications of m-learning, virtual blended environment, administration management and distinguished certification level etc. (Hayyati and Fan, 2010). Threats affectness could be retrieved at last stage using risk assessment phase. The purpose of threat matrix generation is to demonstrate likelihood of occurrence of threats according to level of vulnerabilities for different applications.
- **Threat mitigation:** In this phase, techniques for minimizing the threats are adopted. The purpose is to introduce variety of aspects which describes suitable mitigations (introduction nets) and where to insert them in system with help of advice driven nets in given point cuts. If occurrence of new threats still continues in net after mitigations then

they identified back or restore in previous stage i.e. analysis of threats and then further mitigated.

- **Mitigation correction assessment:** In this phase if the application of incorrect mitigations affects the behavioral properties of net then mitigations are redesigned and changes performed in previous phases. If after application of suitable mitigations chances of risk could evolved then it would be sent to risk-based assessment phase where analysis on threats done for minimization of threats in nets.
- **Mitigation assessment:** The applied or selected threat mitigations behavior could be analyzed and assessed in this phase which determines the accurateness of applied mitigations before and after. Numerical representation is preferred to indicate the threat measure level in system. If the changes found was not significant in numerical value after mitigations applied then it was not preferred. So best suited mitigations techniques would be adopted after returning back to previous stages.

6.4 Methodology on Security Metrics

In this work, methodology proposed by Wang et al. is modified and metric calculation of security features is based CVSS (Common Vulnerability Scoring System). The numerous steps are followed for security measures so they can adapt with SPN related models which emphasized more on learning software weakness. Following eight steps are used to carried out security metrics and related procedures:

1) Vulnerabilities identification in different applications.
2) Severity calculations for different occurred vulnerability.
3) Probabilistic computation of vulnerability occurrence.
4) Threat occurrence and risk assessment computation.
5) Weakness computation against threats.
6) Design and compute security metrics.
7) Calculation of severity of threats after mitigation.
8) Security metrics re-calculation.

Security metric is computed and depicted below with usage of different below equations. The security metric (SM(s)) is calculated by product of severity of weakness (W_n) and risk of corresponding weakness (P_n) as shown in equation 6.1. Here n = 1, 2, 3…., m.

$$SM(s) = \sum_{n=1}^{m}(P_n * W_n) \qquad (6.1)$$

Now, W_n is defined as average base score of its k vulnerabilities, as shown in equation 6.2.

$$W_n = \sum_{i=1}^{k}\frac{V_i}{K} \qquad (6.2)$$

The percentage each representative weakness occurs in the overall weakness occurrences is used to calculate P_n as shown in equation 6.3.

$$P_n = \frac{R_n}{\sum_{i=1}^{m} R_i} \qquad (6.3)$$

Where R_n is the frequency of occurrences for each representative weakness in the SPN as shown in equation 6.4, where K is the number of weaknesses and A is the sum of affected nodes in SPNs.

$$R_n = \frac{K}{\sum_{i=1}^{m} A} \qquad (6.4)$$

To make the value of SM(s) value to range from 0 to 10 is required to hold for P_n.

$$\sum_{n=1}^{n} P_n = 1 \qquad (6.5)$$

The severity of each weakness in e-learning systems after mitigation is recalculated as shown in equation 6.6. Here E denotes Exploitability, RL denotes Remediation Level and RC for Report Confidence which are important temporal metrics of CVSS. CR denotes Confidentiality Requirement, IR denotes Integrity Requirement and AR denotes Availability Requirement which are environmental metrics of CVSS.

$$W_{n_{new}} = \sum_{i=1}^{k}\frac{V_i * E * RL * RC}{K * CR * IR * AR} \qquad (6.6)$$

For each mitigation weakness, if there exist certain vulnerabilities that still occurred are identified by recalculating equation 6.4. If the number of affected nodes become same compared to the results obtained after applying mitigations, then security metric has to be recalculated with help of equation 6.1. The proposed system intended to identify threats and their analysis in design and analysis phase, therefore the number of nodes affected in the SPN will be compromised due to threat occurrence is used. To re-compute the threat's severity after applying the mitigation CVSS based equation 6.6 is added for solving computations.

The proposed framework modules have been applied to case study on modeling of Question–Answer system for Udutu based e-learning system. (Sherief et al. 2010) developed their threat framework and applied their framework on AI specific question answering system which is different from our question answering system.

Decompose Application

The Java driven question answer application is used in system which allows user to ask different questions answers related to programming and expect answer from user end in subjective and objective manner. Once the authentication is completed by user end who allowed to enter questions on programming constructs. The system tried to find whether answer related to questions exist in direct manner or not. If direct solution to questions available, then it could be fetched or obtained easily from knowledge base and shown. Otherwise, keyword based optimized search approach was deployed for finding answer possibilities which are available in knowledge base. Based on data availability, creation of answer formations would be done and out of available solutions retrieve the best possible answer for user and display the appropriate one according to suitability and needs.

The processing of input data and modeling of petri net model governs the designing part of SPNs through randomized events. The Petri net modeling is shown in Figure 6.4 in which initial marking starts by one token in P0 that carries out different values throughout the transition firings from one place to another.

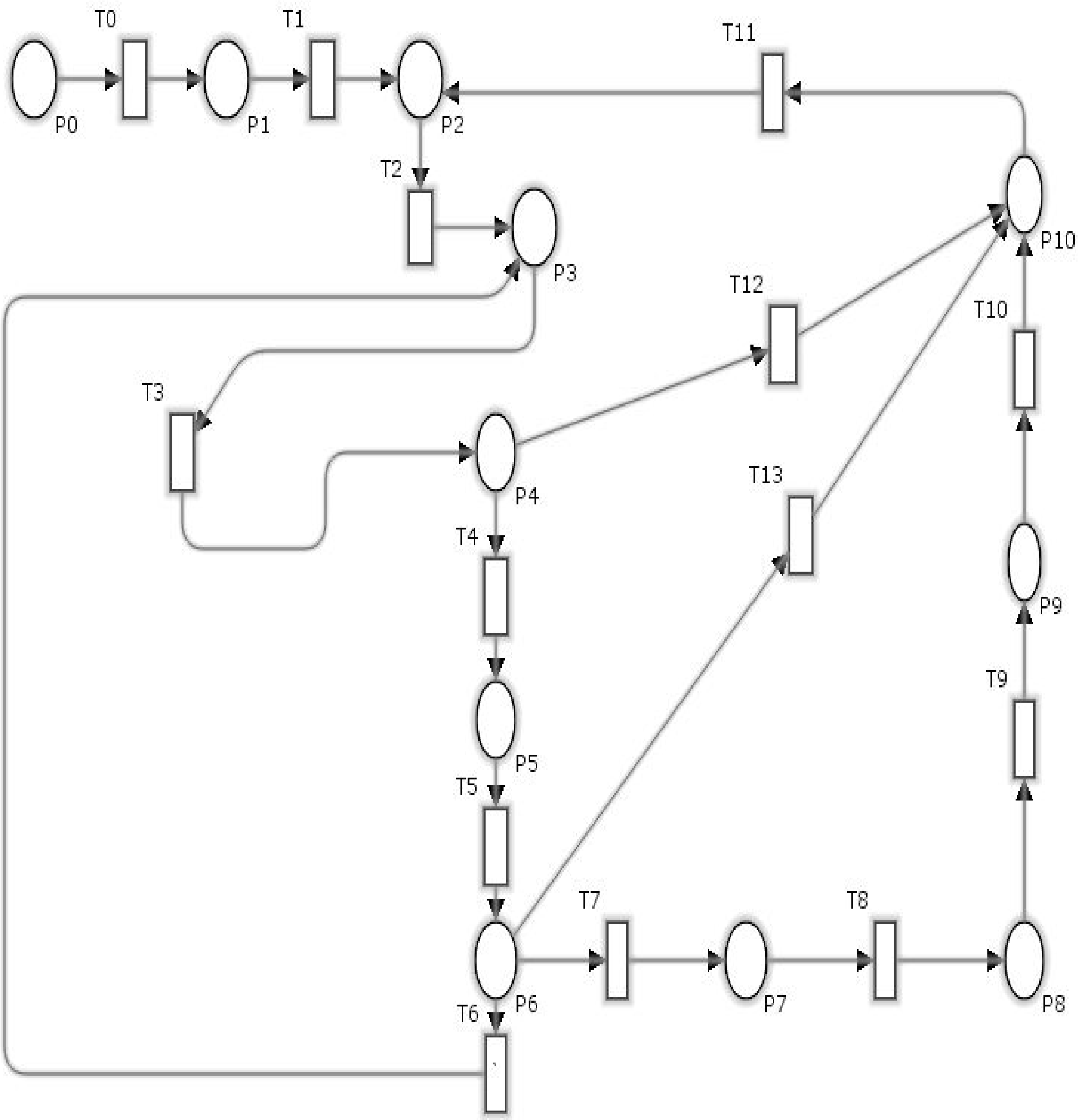


Figure 6.4 Petri net model for question answering system

For better understanding of above depicted model, meanings of places and transitions are shown in Table 6.1 respectively.

Table 6.1 Place and Transitions for Question Answer System

Place Number	Place Description	Transition number	Transition Description
P0	User login	T0	Authenticate
P1	Authenticated/Authorized	T1	Go to main page
P2	System Ready state	T2	Enter an objective question
P3	Objective Question Asked	T3	Search if a direct objective answer exists
P4	Direct Answer Yes/No	T4	Enter a subjective question
P5	Subjective Question Asked	T5	Search if a direct subjective answer exists
P6	Direct Answer Yes/No	T6	Searching the data in objective question knowledge base
P7	Data found	T7	Create the answers
P8	Answer formed	T8	Select from the answers
P9	Answer Selected	T9	Display an answer
P10	Response displayed	T10	Getting response from answers
		T11	Exit
		T12	Decrypt answer formation decision and retrieve direct response for objective
		T13	Decrypt answer formation decision and retrieve direct response for subjective

Decomposition Correction Assessment

There are mainly three properties like reachability, liveness and boundness are required for checking correctness assessment for e-learning systems. Reachability is used to check whether given state is reachable from one end to another (Haas, 2002). SPNs couldn't contain more than k tokens in their entire cycle which are bound towards petri net system. Liveness predicts that state cannot stucked into deadlock and if it is reachable can be fired at any time instant. The reachability graph shows in Figure 6.5 shows the different markings and various states of SPNs that can be reached. Safe SPNs are usually single bounded and live driven learning systems. As shown in Fig 6.5, various markings are depicted where arcs got labeled with different transitions and reached some stage through transactions firing.

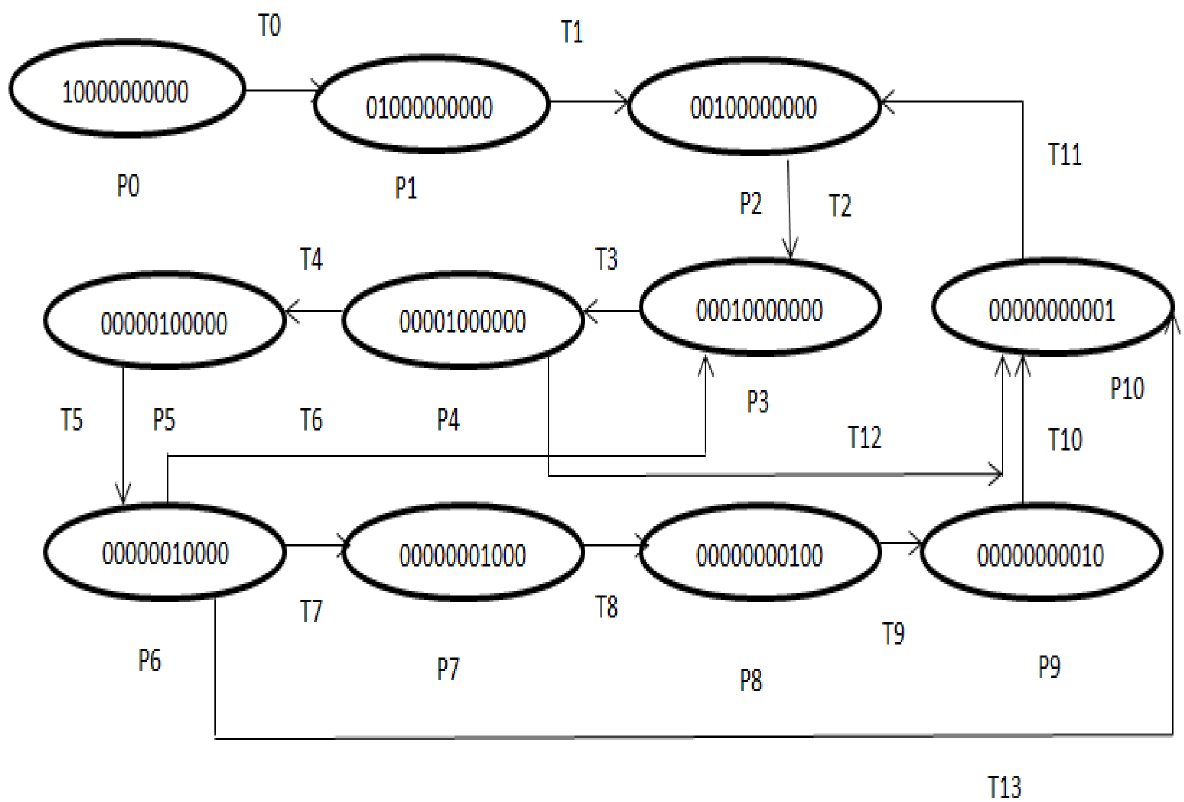


Figure 6.5 Reachability graph for SPNs of Question Answer System

Analysis of threats

The described framework is divided into three phases as identification of threats, application vulnerability and assessment of risks.

Threats identification:

In proposed case study on e-learning systems different variety of threats need to be mitigated at early stages. There are severe chances of getting authentication level vulnerability due to present of several threats like guessing of password, reply from cookie, network eavesdropping as user signed into system. During searching of direct answer exists or not the data tampering would be done by attacker which change the formulation code. Third, if unauthorized user attempts to decrypt the formation of answers and find for direct response received by display then privilege of elevation could occurred. Finally, while formation of answers from collected data, an attacker could tamper or destroy the data and creation of answers could be affected.

The identification of different vulnerabilities related to security for distinguished applications in e-learning system were detected and threats is being analyzed and assessed with help of risk assessment matrix (Hayaati and Fan, 2010). The occurrence of likelihood and system impact is governed by risk of individual threats. (Barbeau, 2005) proposed risk evaluation grid which is used to evaluate risk through risk evaluation phase. The risks obtained from different threat analysis which classified into three different group as minor, major and critical which are decided by an expert. The e-learning threats risk matrix for different threats is as shown in Table 6.2.

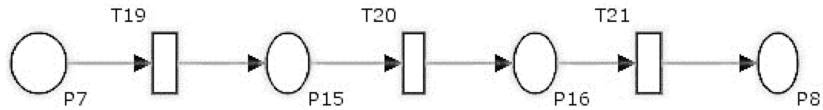
Table 6.2 Threat Matrix

	Legend		E-learning Applications									
	CR	Critical	VLE									
	MA	Major	Online course admin		Course management	Communication tools						
	MI	Minor										
		Not relevant										
No	Vulnerability Category	Threats	Course learning	Grading center	Deliver learning content	Online session	Email	Personal Portfolio	File storage	Assessment tool	Mobile learning	Virtual library
1	Input & data validation	Buffer overflow	MI	MA	MA	MI	MA	MI	MA	CR	MA	MI
2	Authentication	Network Eavesdropping	MI	CR	MI	MI	MA	MA	MA	CR	MA	MI
3	Authorization	Elevation of privilege	MA	CR	MA							
4	Encrypt response decision	Change response formation mode	MA	MA	MA	MI	MI	MA	CR	CR	MA	MI
5	Encrypting system call arguments	Influence answer creation	MI	MA	MI	MI	MA	CR		CR	MI	
6	Auditing and logging	Malicious code	MI	MI	MA							MI

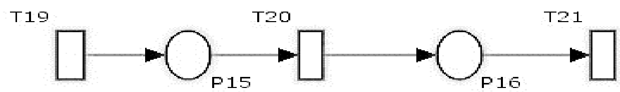
Mitigate threats

STRIDE is helpful for different threat categories identification. As shown in Figure 6.6 different aspects for tampering with data threat is encircled for mitigation of threats. The data tampering is mitigated to prevent code injection attach to influence answer creation with help of encryption technique (Wang et al. 2009). In Figure 6.6, T19 represents the encrypting system call arguments (Oyama., 2006); P15 represents the system state where calls encrypted to prevent the data tampering and attacks; P14 place denotes the decryption and encryption of arguments; P16 state indicates the answer completion and formation; and T21 depicts decrypting the system call arguments. There are other threats like elevation of privilege threat will be mitigated by authorization and authentication mitigates network eavesdropping. For given aspect of data tampering threat the pointcut is T8; the advice net and introduction net will be

Advice net:



Introduction net:



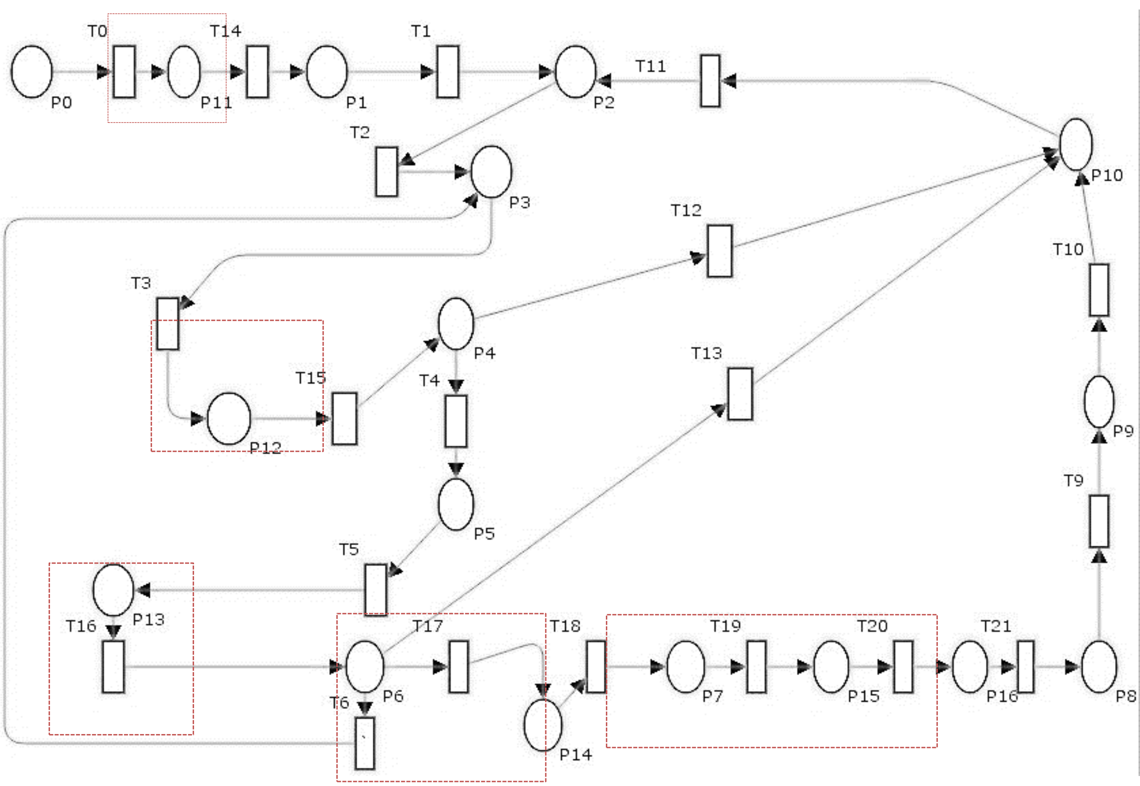


Figure 6.6 Petri net model after threat mitigation

6.5 Security Metrics Calculation (Mitigation Correction Assessment)

Vulnerabilities Identification

There are various types of weaknesses exist in e-learning systems like network eavesdropping; change response formation mode; influence answer creation and elevation of privilege.

Computation of severity level

Different values are assigned to individual base metrics for computation of CVSS which are helpful in creation of base vectors given as:

1) Network eavesdropping: The base vector will be AV: [A] / AC:[H] / Au:[S] / C:[N] / I:[N] / A:[P] = 1.5
2) Change response formation mode: The base vector will be AV: [A] / AC:[H] / Au:[S] / C:[N] / I:[C] / A:[N] = 4.3.
3) Influence answer creation: The base vector will be AV: [A] / AC:[H] / Au:[S] / C:[C] / I:[C] / A:[P] = 6.2
4) Elevation of privilege: The base vector will be AV: [A] / AC:[H] / Au:[S] / C:[C] / I:[N] / A:[P] = 5

Probabilistic computation of different vulnerabilities

The occurrence of vulnerability and related probabilities could be computed by identification of several weakness and major vulnerabilities which exist in software. These calculations are computed or obtained from equation 6.4 (R_n). 1) Network eavesdropping: $R_1 = 1/20$, 2) Change response formation mode: $R_2 = 1/20$, 3) Influence answer creation: $R_3 = 1/20 + 1/20 = 1/10$, 4) Elevation of privilege: $R_4 = 1/20 + 1/20 + 1/20 = 3/20$.

Individual weakness computation

The percentage of each weakness in the software is calculated from equation 2 (W_n) and equation 6.3 (P_n). 1) Network eavesdropping: $P_1 = R_1/ (R_1 + R_2 + R_3 + R_4) = 0.15$, 2) Change response formation mode: $P_2 = R_2/ (R_1 + R_2 + R_3 + R_4) = 0.15$, 3) Influence answer creation: $P_3 = R_3/ (R_1 + R_2 + R_3 + R_4) = 0.28$, 4) Elevation of privilege: $P_4 = R_4/ (R_1 + R_2 + R_3 + R_4) = 0.42$.

Calculate security metric

The outputs of equation 6.2 and 6.3 are require to substituted in equation 6.1 to obtain the security metric value. The security metric score is calculated based on equation 6.1:

$$SM(s) = W_1{*}P_1 + W_2{*}P_2 + W_3{*}P_3 + W_4{*}P_4 = (1.5{*}0.15 + 4.3{*}0.15 + 6.2{*}0.28 + 5{*}0.42) = 4.7.$$

Threats severity computation after mitigation

The obtained security metric need to be recomputed for gaining a comparative analysis of states before and after applying mitigations. The computed values obtained after mitigation would be less than the values obtained before mitigations.

The creation of temporal vector with help of values assigned to temporal metrics facilitates calculation of CVSS driven score which should be computed for individual mitigated threats. Fir different threats the temporal score would be computed which is given as:

1) Authentication: The temporal vector will be E: [F] / RL:[W] / RC:[C] = 1.35
2) Encrypt response decision: The temporal vector will be E: [POC] / RL:[W] / RC:[UR] = 3.5
3) Encrypting system call arguments: The temporal vector will be E: [H] / RL:[W] / RC:[C] = 5.9
4) Authorization: The temporal vector will be E: [F] / RL:[W] / RC:[C] = 4.5

The consideration of confidentiality requirement (CR), integrity requirement (IR) and availability requirement (AR) (Heyman et al. 2008) metrics are taken into account for calculation of $W_{n_{new}}$.

The environment metrics for identified threats are:

1) Authentication: The required environmental vector will be CR:[M] / IR:[H] / AR:[H]. Where M is 1.0, H is 1.51.
2) Encrypt response decision: The required environmental vector will be CR: [H] / IR:[L] / AR:[M]
   Here M is 1.0, H is 1.51 and L is 0.5.
3) Encrypting system call arguments: The required environmental vector will be CR:[H] / IR:[H] / AR:[M].
4) Authorization: The required vector will be CR: [M] / IR: [H] / AR: [H].

From equation 6.6 the new obtained value for $W_{n_{new}}$ need to be calculated which gives new value for severity of weakness after applying mitigations as:

$$W_{n_{new}} = \frac{1.35}{(1 * 1.51)} + \frac{3.5}{(1 * 1.51 * 0.5)} + \frac{5.9}{(1.51 * 1.51 * 1)} + \frac{4.5}{(1 * 1.51 * 1.51)}$$

Security metrics recalculation:

The security metric score SM(s) could be computed based on equation 6.1 after substituting $W_{n_{new}}$.

$$\text{SM(s)} = P1 * \frac{1.35}{(1*1.51)} + P2 * \frac{3.5}{(1*1.51*0.5)} + P3 * \frac{5.9}{(0.5*1.51*1)} + P4 * \frac{4.5}{(1*1.51*1.51)}$$

$$= 0.15 * 0.59 + 0.15 * 4.63 + 0.28*2.58 + 0.42*1.97 = 2.33.$$

Before applying mitigations, the security metric value obtained was 4.7 whereas after successfully mitigating threats the security metrics was again recomputed which checks effectiveness of mitigations applied and security metric value obtained was 2.33. Based on occurrence of threats and applied mitigation were very effective in places where they had applied. The mitigations effectiveness could be analyzed on basis of security metric values and demonstrate complete analysis between different mitigations.

6.6 Performance Evaluation

Two existing frameworks proposed by (Howard, D.L 2003) and (Sherief et al. 2010) was compared with our security driven threat modeling framework. Framework proposed by Howard only considers base metrics whereas (Sherief et al. 2010) framework involves both base and temporal metrics for threat severity measurement. Our proposed framework considers base, temporal and environment metrics and achieved better results and accuracy compared to other traditional frameworks. The comparative views of threat driven frameworks are shown in Table 6.3.

Table 6.3 Comparative view of various threat driven frameworks

Author	Modeling	Used Framework	Proposed Metrics
(Howard, D.L 2003)	NA	Three modules are used in framework as application decomposition, threats identification and mitigation of threats at different level.	Base metric is used to compute severity measure as: $W_{n_{new}} = \frac{V_i}{K}$

(Sherief et al. 2010)	Stochastic based	Mainly six modules are used as: application decomposition, correction assessment, threat identification, mitigation of threats, correction mitigation assessment and mitigation assessments.	Base and temporal metrics are used to calculate severity measure $W_{n_{new}} = \frac{V_i * E * RL * RC}{K}$
Our proposed approach	Aspect oriented stochastic petri nets	Identification of threat is divided into different modules as: 1. Disintegrate application. 2. Disintegration correction assessment. 3.1 Identification of threats. 3.2 Vulnerability identification 3.3 Matrix assessment (Risk based) 4 Threats mitigation 5 Mitigation assessment correction 6 Mitigation assessment	Base, temporal and environment metrics are used to compute severity of metrics as: $W_{n_{new}} = \frac{V_i * E * RL * RC}{K * CR * IR * AR}$

6.7 Related works and Comparative view of methods

In proposed system threats are mitigated by introducing modified threat driven framework which involves stochastic aspects and petri nets usage which further computes security metrics for network assessment. The mitigation and threat identification are done by threat modeling process. The applications are being decomposed into different layers then threats are ranked according to their severity. The objective is to choose most better way for threat mitigation and adapt suitable methodology for techniques which are identified.

During designing of secure system variety of UML driven security related policies are delivered by aspect-oriented system (Dehlinger and Nalin, 2006). The different review on secure framework is provided to several authors for their usage and design. The prime concern of software is to maintain its integrity, confidentiality which is achieved through aspect driven nets (Xu and Naygard, 2006). The authors recommended approach categorized the modeling of software and threat mitigations by effective usage of petri and aspect-oriented nets.

The behavior of model mostly dependent on structures but timing also played a major role for better accuracy. Haas introduced transition randomness based non-deterministic system i.e. stochastic petri nets (SPNs) (Haas, 2002). Modeling of such model require exponential distribution and overall performance is gathered through Markov theory utilization. Variety of advantages of SPNs obtained over conventional petri nets like graphical mode is used for functional testing and analysis, concurrency to be scheduled is described and synchronization obtained through usage of different activities and their correlation. These activities are responsible to maintain the quantitative and qualitative system attributes which determines when to fire token, at how many places token should be fired and total amount of token expected to receive from one place to another at specified time intervals etc.

Major challenge and problem faced by researchers over last decade is to identify major security loop holes over network. Variety of security metrics and related areas demonstrated by NIST which advanced the state of art through calculation of security metrices (Jansen, 2009). Different estimations based on different level metrics like low and high scale related to security has been performed. SODAWeb is security tool which filters different related adaptive techniques integrates and operates several tools at once (Jansen, 2009). (Heymen et al. 2008) discussed combination of different security metrics achieved through usage of security patterns.

We have adopted Common Vulnerability Scoring System (CVSS) (Mell and Romanosky, 2007) in our integrated security framework model which involves three groups: Base, Temporal and Environmental. Individual groups represent different numeric scores ranges from 0 to 10. A new approach was proposed by (Wang et al. 2009) for identification of existing vulnerabilities and improvement in software quality and related systems. The approach discussed was modified and utilized effectively in e-learning systems. It uses the Common Vulnerabilities and Exposures (CVE) and CVSS in calculation and defining metrics are different level. A complete comparative view of similarity and differences of proposed method with existing methods are given in Table 6.4.

Table 6.4 Similarity and differences of proposed method with existing models

Author	Proposed Method	Similarity	Differences
Dehlinger and Nalin (2006)	UML based aspect-oriented model	Preferred aspect nets	Not considered CVSS attributes for defining software modeling and threats mitigations.
Omrani et al. (2011)	High level petri nets used and involves learners style, knowledge and score level.	Performance of e-learning systems get evaluated.	High level petri nets used without threat consideration but our proposed model used SPNs which improves system robustness and performance before and after mitigation.
Balogh et al. (2012)	Deliver learning content to student according to their need and knowledge level with help of petri net LMS.	NA	System reliability and consistency improved without using security metrics and emphasize on personalized petri nets.
Hammami et al. (2013)	E-learning system developed using multi agent and adaptive systems.	NA	Objects petri net adopted to build adaptive e-learning system which delivers content according to individual needs and preferences.
Kaur et al. (2016)	Analyze behavioral and structural property of system and perform threat mitigations in software	Aspect oriented nets	Behavioral and structural analysis identified using Farkas method of invariance

	systems		computation.
Malik and Pandey (2017)	A discrete event-based threat driven secure model was built to provide secure communication among RSUs in vehicular network	NA	Reachability and liveness property is acquired by proposed RSU driven framework.

6.8 Conclusion

The purpose of chapter is to provide an efficient secure framework which identifies threats and proposed different security enabled metrics with help of Vulnerability scoring system and aspect oriented stochastic petri net models. In the proposed framework different phases of assessments were involved like mitigation examination measures correctly the behavioral properties of aspect and stochastic oriented petri net models whereas the effectiveness of mitigation applied is measured or obtained by assessment of attenuated phase. These additional usages of stochastic governed petri models introduced introduction, point cut and advice nets into existing system network. The computed metrics related to security for different stochastic nets is evaluated with help of common vulnerability scoring system and different metrics like temporal, base and environmental enables metric computation after application of mitigations and perform comparison over existing metrics.

Chapter 7

Performance Evaluation

7.1 Introduction

Due to rapid growth of advanced internet and educational technologies, e-learning is considered as pioneer field of investigation and study. The traditional aspects of learning provide simplex mode of learning where focus and emphasis were not given on individual learner's skills, background interest, motivational features, needs and goals which sometimes badly affect the learning performance and overall grooming of learner. Such types of emerging problems and issues are being handled by adaptive methods which improves dynamically the overall performance and behaviour of system on basis of strategic feedbacks obtained from stimulus and flexible e-learning environment.

With huge development of e-learning systems (eLS) it becomes essential to evaluate the quality of service of e-learning system and their performance, but till date there is no standard available to evaluate the performance of such system.

In performance analysis, two aspects are being covered: to evaluate service quality of e-learning systems and overall system performance of these systems.

Aspect 1: To evaluate quality of service of eLS by using QoS and Cognitive (CoG) parameter-based Uncertainty model for E-learning service selection.

The heterogeneous systems inter and intra operability could be governed with appropriate quality of service by providing suitable architecture to relate different applications. The process of data exchange with help of XML and web format could be facilitated with help of web applications and integrated end products. These service applications are modular, distributed and dynamic in nature which can be published, described and located over web network.

The stated work is published in: Aditya Khamparia, Babita Pandey.: A QoS and CoG parameter-based uncertainty model for selection of semantic web services. In: Indian Journal of Science and Technology, Vol. 9, issue 44 (2016).

Due to enormous wider applicability, availability and adaptability of different web services they could create problem in service discovery, matchmaking, orchestration and selection of specific services which meets user criteria and needs. Semantic web converts web data into meta processable machine data and explains explicit information governed by various services.

The most significant construct of web service composition process is web service selection. Various composition processes such as: discovery, selection, composition, orchestration and choreography, and matchmaking are dependent on QoS and CoG parameters (Kumar and Mishra, 2008). The service is described with help of QoS whereas Semantic Web Service (SWS) deciding factor role could be better played by CoG parameters. These parameters are responsible to invoke appropriate service from the available number of discovered services and compute parameters.

The literature survey which studied reveals that amount of uncertainty exists among CoG and qualitative parameter were not encountered by researchers. Due to this, as of now no generic centered process were suggested by researchers, mainly because of two important reasons: 1) QoS metrics complexity; 2) lack of formal measurement of CoG parameters. (Kumar and Kumar, 2009) proposed Hybrid Selection Model (HSM) which provides the normalized QoS and CoG service parameters which provides a dynamic feedback system affecting the service provider reputation based on service quality they offered.

In proposed work, on the basis of expert feedback, a rule base model (RBM) has been deployed. The model selects the SWS based on qualitative (QUAL) and quantitative (QUANT) parameters. Quality of services (QoS) parameters such as: integrity (In), benevolence (B), experience (Exp), adaptability (Ad), expertness (Ex), credibility (Cr) are QUANT parameters whereas CoG parameters such as capability (C), desire (D), commitment (Co), trust (T), persuasion (P), emotions (Em) and reputation (R) are QUAL parameters. The RBM generated from the hierarchal structure is used for computing cumulative certainty factor (CCF) of each QUAL and QUANT parameters. The model also deals with the uncertainty lies in the both QUAL and QUANT parameters. This is a generic model independent on types of SWS and deals with uncertainty lies among the QoS and CoG parameters.

Aspect 2: To evaluate Overall performance of eLS by using Importance, Complexity and Performance Index.

The performance of eLS could be evaluated by researchers on various parameters listed as: prediction accuracy (Minaei et al., 2004), concept relation degree (Chih-Ming et al., 2006), experimental pre and post test analysis (Yang et al., 2008; Khamparia and Pandey, 2014; 2015; Pandey et al., 2014), satisfaction degree (Liang et al., 2008), Felder index learning style (Norwawi et al., 2009), standard and peer review method (Encheva et al., 2006), teaching and course content cost with analysis (Wang et al., 2009). (Wang and Liao, 2011) used experimental and control group tests and coefficients correlation and related accuracy (Seters et al., 2011) for eLS. The methods listed by different researchers are not generic in nature and the performance of other eLS could not be judged by their capability due to their constraint available in parameters which exist for once system but not available in other systems. They also not imbibed the measuring cost of student’s features or predictors and also fail to evaluate system performance on the basis of importance and complexity level involved in deploying and maintenance of system. Whereas, while measuring a system it is very important to consider the tradeoff among the performance (Performance Index (PI)), importance (I) and complexity (CC) involved in the system. Individual system performance could be compared on basis of stated factors. Therefore, in stated work, we have developed a new method for evaluating the performance (PI) of eLS based on these two factors.

The stated work is published in: Khamparia A., Pandey B. Performance Index assessment of intelligent computing methods in e-learning environment. In International Journal of Advanced Intelligence Paradigms, (Article accepted and available in Forthcoming article list)

7.2 Limitations of Existing Model

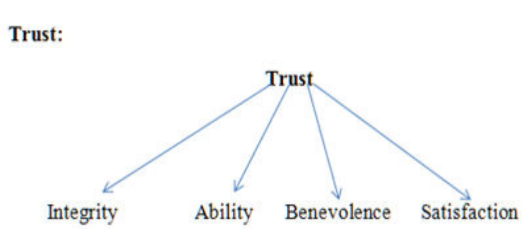
The uncertainty lies in different CoG parameters does not governed by existing models. There are some sources of uncertainty which lead to uncertainty in CoG parameters like machine which refers to some predicted system, environment in which predicted machine system works, man is the cognition subject of machine environment system. Every source relies on data collection, data preprocessing and assessment of failure criteria which leads to uncertainty in CoG parameters (Keskes, 2013). The existing models either deal with only few qualities of services parameters such as: T, Cr, In and B or CoG parameters such as Em and Ad but no model deals with both types of parameters and uncertainty lies among them. Our intent is to propose a model which prefers available web services on the basis of service quality and CoG parameters and describe the amount of uncertainties lies among parameters.

7.3 Aspect 1: CoG Parameters and their Hierarchical Relationship

As discussed above all the CoG parameters such as T, R, In, Co, C, B, D, Em, Cr, P, Ad, Ex and Exp play important role in the semantic web service selection. These CoG parameters are hierarchal dependent on each other. In this section, we have developed a hierarchical model of CoG parameters.

The CoG parameters T is described by Lewicki and his colleagues as an individual belief in, and willingness to act on the basis of word, actions and decisions of others. R is a socially transmitted meta-belief concerns property of agents such as: attitudes towards some socially desirable behavior, reciprocity or non-compliance. **C** is a parameter which enhances the strength of dedication (De), D, T, Ad (Dixit and Sachan, 2013). B is a kind of trait which is important for establishment of interpersonal trust. It is helpful in assessing trustworthiness of system in service of decisions about appropriate reliance and delegation. C is used in context of service provider to provide capability of service provider. It is considered as combination of source expertness of knowledge, perception of knowledge expertise, openness and honesty, concern, care and trust worthiness of source. P is an extent to which attitude, belief, reputation and intention can be changed. E is state of mental readiness which provides an evaluation of objects and events arises from CoG appraisals of thoughts and events. D is a motivational state directed at either goal or an act or sense of lodging for a person or object hoping for outcome. Exp determines the number of times service requested and used by user. More experience of service leads to best selection. I determine the accuracy of service provider to provide best service.

The hierarchical relationship among various CoG parameters such as T, R, In, Co, C, B, D, Em, Cr, P, Ad, Ex and Exp on their sub parameters are shown in Figure 7.1. From Figure 7.1, it was clear that T was hierarchically dependent upon In, Ad, B and S. The certainty factor (CF) of T, was calculated by cumulating the CF of integrity, ability, benevolence and satisfaction. This computed value gave belief or degree of satisfaction of T. R was hierarchically dependent upon uniqueness, attributes and admireness, commitment and advocacy, cooperation. Cr was hierarchically dependent upon trust, expertness of service, perception of openness and honesty and perception of concern and care. P was hierarchically dependent upon belief, attitude, intentions and behavioral motivations as shown in top middle part of Figure 7.1. In was hierarchically dependent upon consistency of past action, credibility of communication, commitment to standards of belief and congruence of other words and deeds. Co was hierarchically dependent upon dedication, desire, ability, motivation, will power. Ex was hierarchically dependent upon reliability, technical skills and experience. Ad was hierarchically dependent upon cost, capability delivered and demanded and time delivery. As shown in top right most part of Figure 7.1, B was hierarchically dependent upon honest and open communication, delegating decisions and sharing control to others. C was hierarchically dependent upon perception processing, planning, anticipation, capacity. D was hierarchically dependent upon pleasure, will power, dependency, capability, emotions. Exp was hierarchically dependent upon A, R and Co and finally Em was hierarchically dependent upon greed, lust, anger, desire, willingness, regret, curiosity.



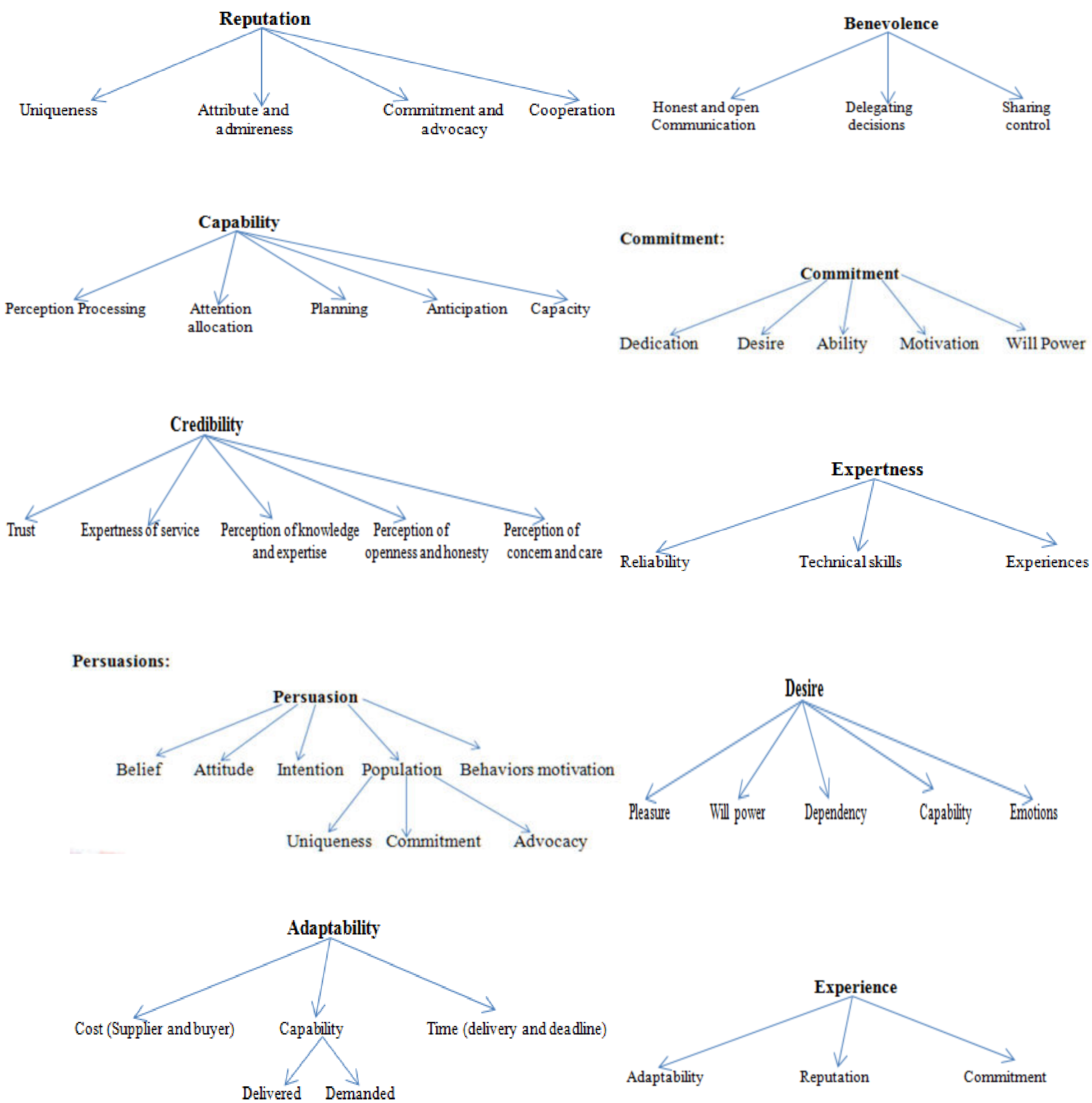


Figure 7.1 Hierarchical relationship among functional attribute and various CoG parameters

Figure 7.2 represents individual and established relationship among different parameters of CoG importance. In the figure, the satisfaction level (S) of user is denoted by root which lies between 0-1.If the achieved certainty factor at root node is either 1or 0 then it is satisfactory and unsatisfactory. The satisfaction level is represented by equation 1.

$S\,[0, 1] = \{x: x \varepsilon [0, 1]\}$ - - - - - (1)

$x = 0$ then unsatisfactory

$0<x<1$ degree of satisfaction

$x=1$ then satisfactory

The value between 1 and 0 tells the degree of satisfaction. The threshold value to be considered is 0.8 if obtained values is less than threshold then it leads to unsatisfaction otherwise it become satisfaction.

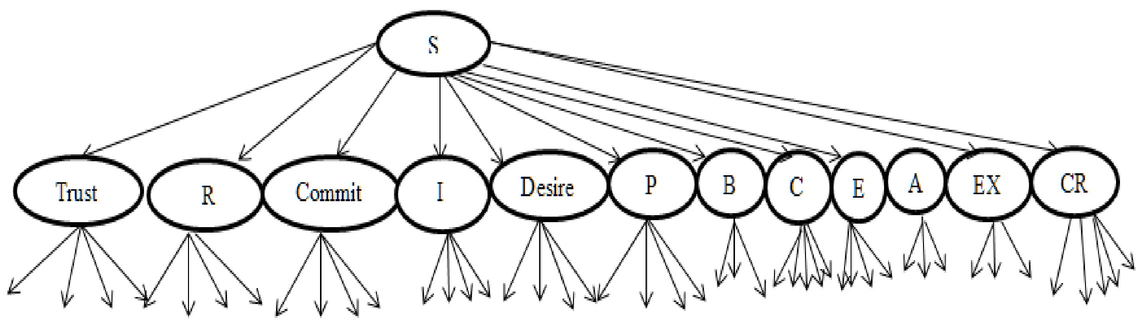


Figure 7.2 Hierarchical models of CoG parameters for web service

Rule based Model

Based on expert consultancy and literature survey the hierarchical and rule-based model was formulated as shown in Figure 7.3. It shows modular representation of facts and information. The leaf nodes in hierarchical tree shown in Figure 7.3 are represented using symbol R_{xyz} such as:R_{111}: I, R_{112}: A, R_{113}: B, R_{114}: SR_{141}: consistency of past action, R_{142}: credibility of communication,R_{143}: commitment to standard of favors, R_{144}: congruence of other words and deeds,R_{121}: uniqueness, R_{122}: attributes and admireness, R_{123}: commitment and advocacy,R_{124}: cooperation, R_{131}: dedication, R_{132}: desire, R_{133}: ability, R_{151}: pleasure,R_{152}: dependency , R_{153}: willpower, R_{154}: capability, R_{155}: Em, R_{161}: belief, R_{162}: attitude, R_{163}: intention, R_{164}: population, R_{165}: behavior motivation , R_{171}: honest and open communication, R_{172}: delegating decision, R_{173}: sharing control, R_{181}: perception processing, $R_{182:}$ attention allocation, R_{183}: planning, R_{184}: anticipation, R_{185}: capacity, R_{191}: greed, R_{192}: desire, R_{193}: lust, R_{194}: anger, R_{201}: cost, $R_{202:}$ capability, R_{203}: time, R_{211}: reliability, R_{212}: technical skills, R_{213}: experience, R_{221}: perception of knowledge and expertise, R_{222}: trust, R_{223}: expertness of service, R_{224}: openness and honesty, R_{225}: perception of concern and care. The rules of composition are shown in Figure 7.3.

$$R_{111} \oplus R_{112} \oplus R_{113} \oplus R_{114} \rightarrow R_{11}$$

$$R_{121} \oplus R_{122} \oplus R_{123} \oplus R_{124} \rightarrow R_{12}$$

$$R_{131} \oplus R_{132} \oplus R_{133} \rightarrow R_{13}$$

$$R_{141} \oplus R_{142} \oplus R_{143} \oplus R_{144} \rightarrow R_{14}$$

$$R_{151} \oplus R_{152} \oplus R_{153} \oplus R_{154} \oplus R_{155} \rightarrow R_{15}$$

$$R_{161} \oplus R_{162} \oplus R_{163} \oplus R_{164} \oplus R_{165} \rightarrow R_{16}$$

$$R_{171} \oplus R_{172} \oplus R_{173} \rightarrow R_{17}$$

$$R_{181} \oplus R_{182} \oplus R_{183} \oplus R_{184} \oplus R_{185} \rightarrow R_{18}$$

$$R_{191} \oplus R_{192} \oplus R_{193} \oplus R_{194} \rightarrow R_{19}$$

$$R_{201} \oplus R_{202} \oplus R_{203} \rightarrow R_{20}$$

$$R_{211} \oplus R_{212} \oplus R_{213} \rightarrow R_{21}$$

$$R_{221} \oplus R_{222} \oplus R_{223} \oplus R_{224} \oplus R_{225} \rightarrow R_{22}$$

$$R_{11} \oplus R_{12} \oplus R_{13} \oplus R_{14} \oplus R_{15} \oplus R_{16} \oplus R_{17} \oplus R_{18} \oplus R_{19} \oplus R_{20} \oplus R_{21} \oplus R_{22} \rightarrow R_{1}$$

Figure 7.3 Rule based composition

After performing computation over several levels the final certainty factor or degree of satisfaction is computed at root level which is highest among all available levels. Later various rules deployed for CoG parameters are illustrated.

R_{11}: IF integrity (q1) and IF benevolence (q2) and IF ability (q3) and IF satisfaction (q4) THEN trust (q).

R_{12}: IF uniqueness (q1) and IF attributes and admireness (q2) and IF commitment and advocacy (q3) and IF cooperation (q4) THEN reputation (q).

R_{13}: IF dedication (q1) and desire (q2) and ability (q3) THEN commitment.

R_{14}: IF consistency of past action (q1) and IF credibility of communication (q2) and IF commitment to standard of favors (q3) and IF congruence of other words and deeds (q4) THEN integrity (q).

R_{15}: IF pleasure (q1) & IF dependency (q2) & IF willpower (q3) & IF capability (q4) & IF emotions (q5) THEN desire (q).

R_{16}: IF belief (q1) and IF attitude (q2) and IF intention (q3) and IF population (q4) and IF behavior motivation (q5) THEN persuasion (q).

R_{17}: IF honest and open communication (q1) and IF delegating decisions (q2) and IF sharing control (q3) THEN benevolence (q).

R_{18}: IF perception processing (q1) and IF attention allocation (q3) and IF planning (q3) and IF anticipation (q4) and IF capacity (q5) THEN capability (q)

R_{19}: IF greed (q1) and IF desire (q2) and IF lust (q3) and IF anger (q4) THEN emotions (q)

R_{20}: IF cost (q1) and IF capability (q2) and IF time (q3) THEN adaptability (q)

$R_{21:}$ IF reliability (q1) and IF technical skills (q3) and IF experience (q3) THEN expertness (q)

R_{22}: IF trust (q1) and IF expertness of service (q2) and IF perception of knowledge and expertise (q3) and IF openness and honesty (q4) and IF perception of concern and care (q5) THEN credibility(q).

R_1: IF trust (q1) and IF integrity (q2) and IF reputation (q3) and IF commitment (q4) and IF benevolence (q5) and IF capability (q6) and IF desire (q7) and IF emotion (q8) and IF expertness (q9) and IF persuasion (q10) and IF adaptability (q11) and IF credibility (q12) THEN root satisfaction (q).

The dependency of rule base is mainly on hierarchical arrangement of CoG parameters in tree which could affect rule base structure. Different web service selections are performed on the basis of Shortlifee formula. According to it (Shortlifee and Buchanan, 1984):

If an evidence e1 takes place with hypothesis h then its CF becomes CF(h,e1), similarly another event e2 takes place with hypothesis h then it becomes CF(h,e2). If occurrence of events could be done at same time then calculation of CF could be done using formula which are shown as follows:

MB(h,e1e2) = CF(h,e1) + CF(h,e2) – CF(h,e1)* CF(h,e2) ------------- (7.3.1) Where MB represents measure of belief.

MD(h,e1e2) = CF(h,e1) + CF(h,e2) – CF(h,e1)* CF(h,e2) -------------- (7.3.2)

Where, MD represents measure of disbelief.

7.4 Results and Implementation

The model implementation and deployment were performed in Java based application. Mainly two phases were adapted in service selection model as in the first phase, user selects the CoG and QoS parameters and provides their CF as shown in Figure 7.4. Computation of CCF for different CoG and qualitative parameters were also illustrated in coming phase.

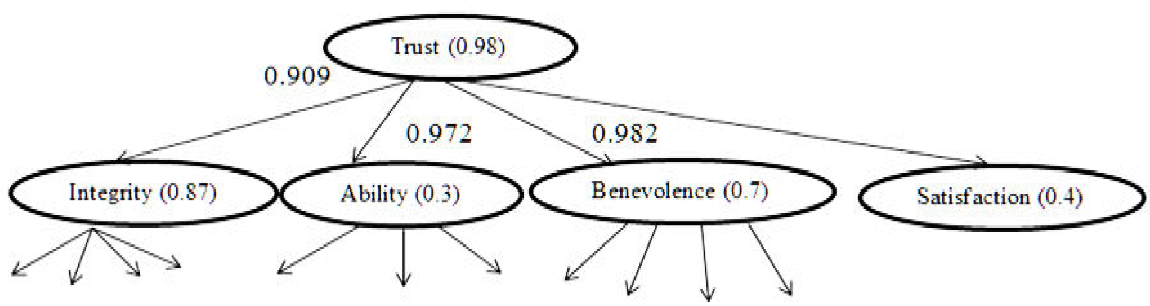


Figure 7.4 Trust CF Calculations

For example, the computation of CCF for trust is done as follows: the user selects the CoG and QoS parameter of trust such as: I (e1:0.87), A (e2:0.3), B (e3:0.7) and satisfaction (e4:0.4). The value in the bracket are read as evidence: CF (evidence:CF). Where e1, e2, e3, e4 is evidence of I, A, B and satisfaction respectively.

For evidence e1 and e2 the certainty factor is computed using equation 1 as follows:

MB = 0.87+0.3(1-0.87) = 0.909

For (e3:0.7),

MB = 0.909 + 0.7(1-0.909) = 0.972

For (e4:0.4),

MB = 0.97 + 0.4(1-0.97) = 0.982

Here measure of disbelief (MD) = 0

So, CCF = MB + MD = 0.982 + 0 = 0.982

This will give the CCF of T i.e. at first level of the hierarchical tree.

Similarly, the CCF for I is computed as follows:

For e1 and e2

MB = 0.5 + 0.2(1-0.5) = 0.6

For e3

MB = 0.6+0.4(1-0.4) = 0.84

For e4,

MB = 0.84+0.3(1-0.84) = 0.878

Here measure of disbelief (MD) = 0

So, CCF = MB + MD = 0.878 + 0 = 0.878.

Similarly, the CCF for other QoS and CoG parameters are computed. The CCF computed for R, Co, D, P, B, C, Exp, Ad, EX, CR are 0.97, 0.97, 0.97, 0.87, 0.90, 0.93, 0.8, 0.9, 0.9, 0.9 respectively as shown in Fig. 7.4.

Now, the CCF of second level i.e. for S was computed as follows:

For two evidence T and R

MB = 0.98 + 0.97 (1-0.98) = 0.99

MD = 0

CCF = MB + MD = 0.99

Similarly, CCF is calculated for other evidences of S which is 0.8. The CCF of S was greater than 0.8 as shown in root of the tree in Figure 7.6, therefore it is acceptable. The pseudo code for computation of CCF is shown in Figure 7.5.

```
Input the certainty factor for integrity (i) & Input certainty factor for ability (j)

While the user has not yet entered the CF

Add certainty factor for integrity and ability to calculate measure of belief or
CCF1

CCF1 = CF (i) + CF (j) (1-CF (i))

Input the next certainty factor for benevolence (k)

Add calculated CCF1 with benevolence (k) to calculate CCF2

CCF2 = CCF1 + CF (k) (1-CCF1)

Increment user value and input next certainty factor for satisfaction (l)

Add calculated CCF2 with satisfaction (l) to calculate CCF3

CCF3 = CCF2 + CF (l) (1-CCF2)

If the calculated CCF3 is less than 0.8

print 'calculated certainty or belief is not acceptable'

else

print 'final combined certainty or belief CCF3 as acceptable'
```

Figure 7.5 Pseudo code for trust CF

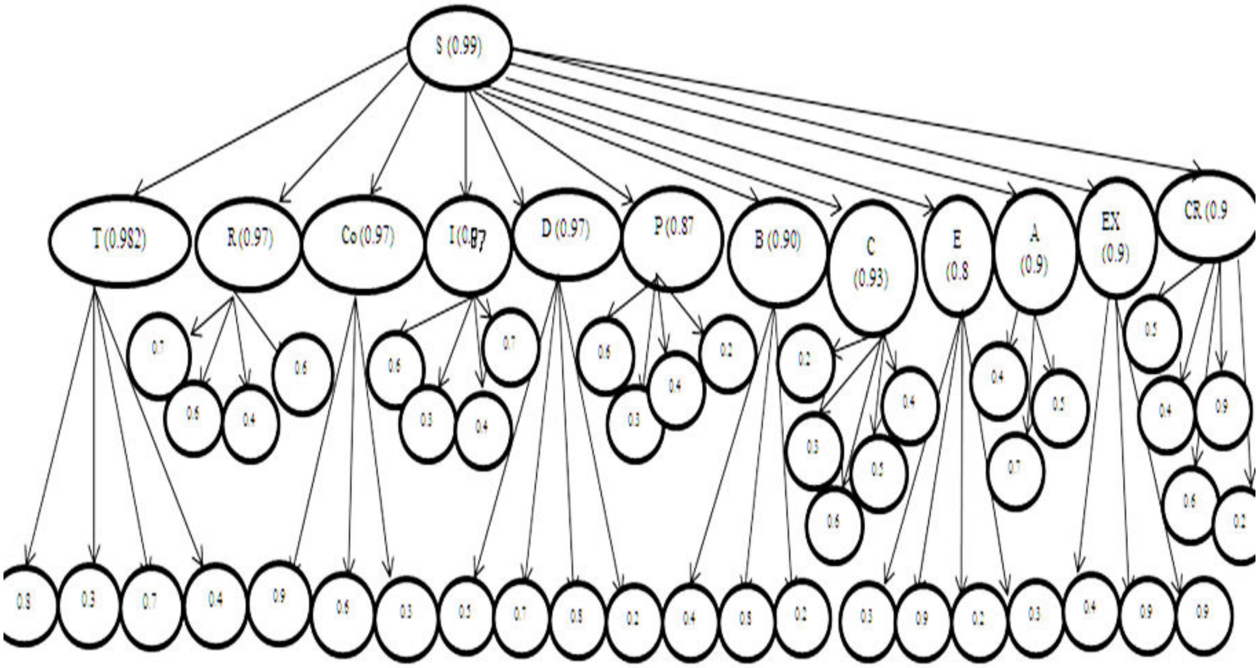


Figure 7.6 Computation of Satisfaction degree

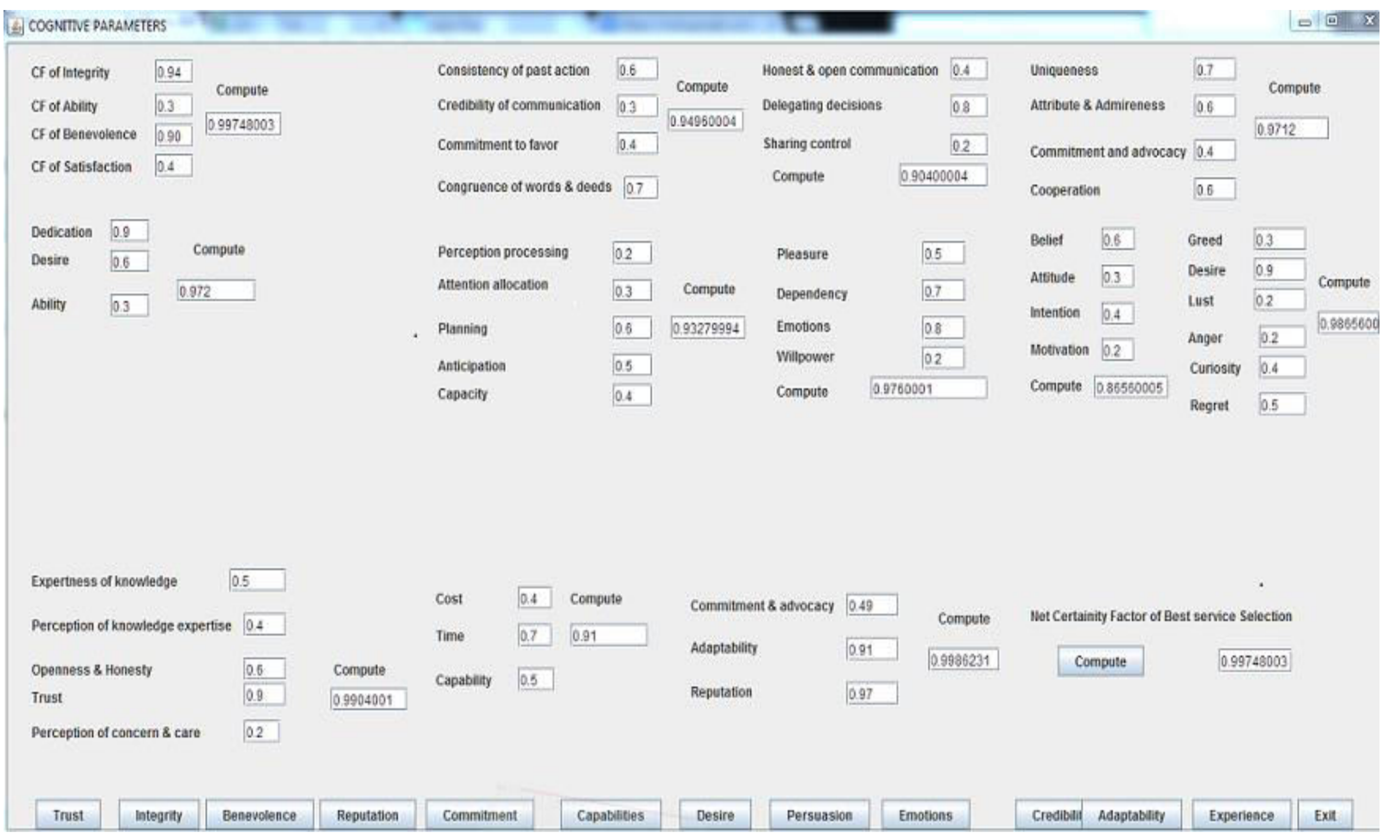


Figure 7.7 Graphical User Interface for inputting the values of CoG and QoS Parameters

Comparison with Existing Bayesian Network Model

The proposed model provides less computational overhead in comparison with model proposed by Nguyen et al. The Bayesian model uses conditional probabilities table in which probabilities are computed for individual web services which takes higher computational overhead and complexity whereas CoG parameter-based uncertainty model has less computational overhead than Bayesian to determine the individual nodes CF computation and provides low overhead to achieve higher satisfaction level. The proposed method facilitates smart and effective selection of services having low computational burden or overhead.

7.5. Aspect 2: Performance Evaluation using Weights and Hierarchy

The complete process of computation of performance index (PI) is shown in Figure 7.8. Based upon the flow of information and step of computation as shown in Figure 7.8, the organization of the work carried out in different sections.

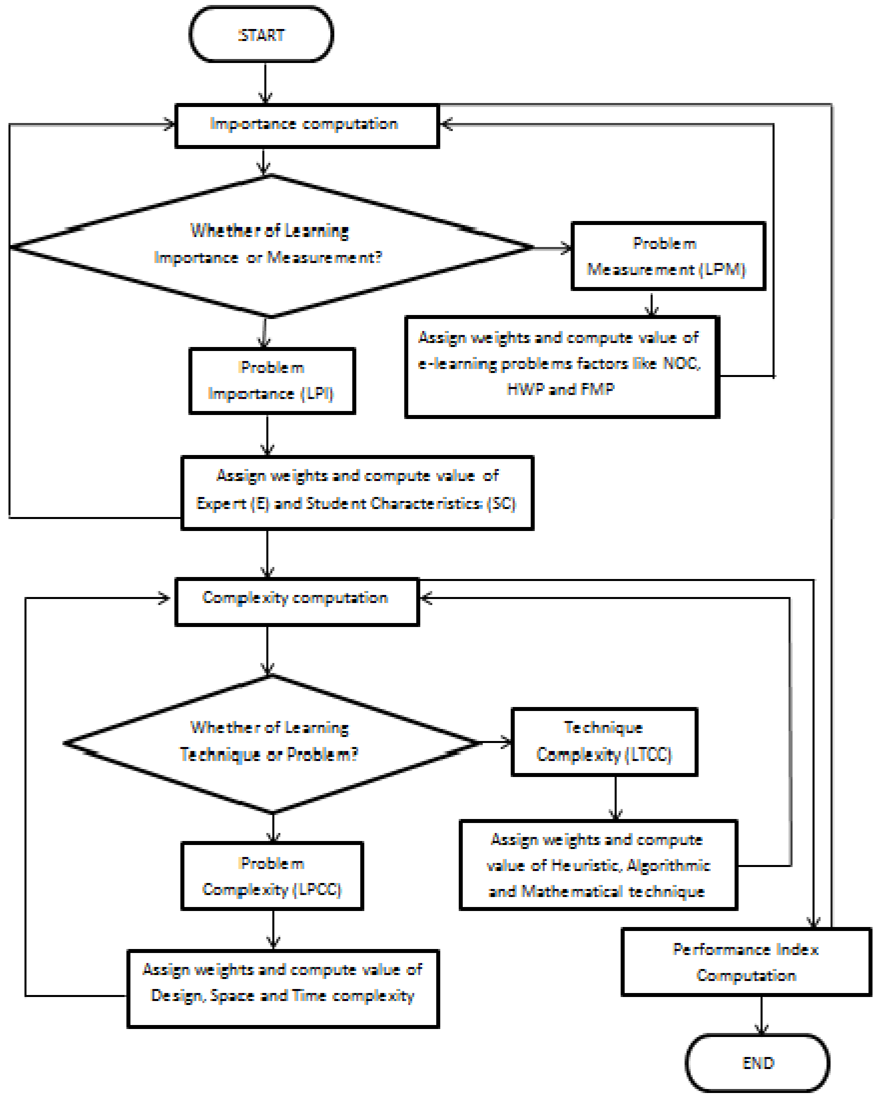


Figure 7.8 Flow chart representation of Performance Index Computation

7.6 Hierarchy of E-learning Problems (ELP)

Based on various literature we have classified the ELP in various group such as: learning path generation (LPG), object recommendation (OR), personalization of content (POC), context learning problem (CLP), information retrieval (IR), domain ontology construction (DOC), classification of learning styles (CLS) (Khamparia and Pandey, 2015). Based on the inclusion of one type of ELP on other a hierarchy is drawn. The weights are assigned to each ELP in hierarchy based on expert suggestion and literatures as shown in Figure 7.9.

In Figure 7.9, the overhead assigned to each level is explained as follows. Suppose that three different courses are available C Programming (CP), Networking (N) and Software Testing (ST). Selection of one course i.e. CP is done by IR. In Figure 7.9, the next level is DOC, the cumulative overhead of DOC was computed by adding the current overhead of DOC (i.e. course structured (CSt), knowledge representation (KR)) and IR. For example, the overhead of IR, CSt and KR are 0.2, 0.1 and 0.1 respectively. Similarly, the third level is POC/CLP problems, the cumulative overhead of POC/CLP problems was computed by adding the overhead of DOC (and additional overhead to determine the CP content and mode i.e. visual, audio, lecture notes) i.e. current overhead of POC/CLP. The cumulative overhead of next level i.e. for OR/CLS was computed by adding the overhead of POC/ CLP (and additional overhead for the topics selection like Arrays (A), Structures (S), Pointers (P) etc.) i.e. current overhead of OR/CLS. For the last level the cumulative overhead of LPG was computed by adding the overhead of OR/CLS (and additional overhead for delivering lecture content in sequence as per their need) i.e. the current overhead of LPG.

In proposed hierarchy, the problem at lower level is dependent upon the problem at higher level. Therefore, the overheads of lower level problem are obtained by cumulative sum of the higher and current level. So, the overhead of lower level ELP is always higher than the previous layer i.e.

$O_i = AO_i + O_{i-1}$

O_{i-1} is the overhead involved in solving the ELP at $i\text{-}1^{th}$ level and AO_i is the additional overhead required to solve the problem at i^{th} level (additional parameters). O_i is the overhead involved in solving the ELP at i^{th} level. The complete overhead at each level is shown in Figure 7.9.

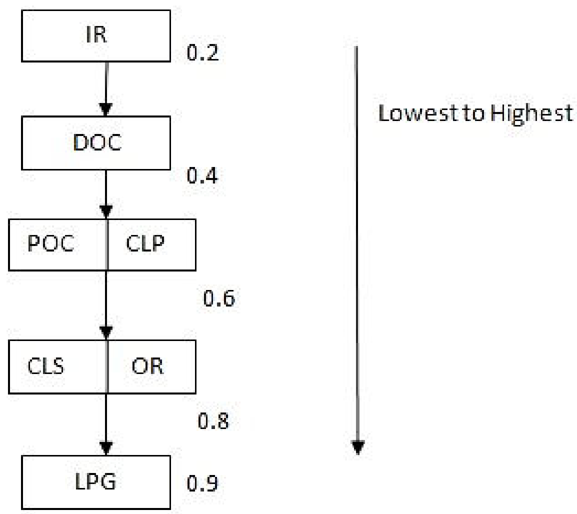


Figure 7.9 Hierarchy of ELP

7.7 Performance Evaluation

This section describes the complete method for computation of PI as followed by different sub sections.

7.7.1 Comparative view of Learning Problem Measurement (LPM)

In this section, various parameters such as: of No. of Problems (NOP), Hierarchical Weight of Problem (HWP) and Factors Measuring Performance (FMP) are computed for various ELP and shown in Table 7.1. In the table, NOP is the total number of learning problem which involved corresponds to every model, HWP indicates dependency of one problem on another and weightage are assigned accordingly, FMP is the importance assigned to individual performance measuring factors such as: prediction accuracy, concept relation degree etc. which are as shown in Table 7.1.

For example, model1 has deployed the K-nearest neighbour and genetic algorithm and ELP is CLS as shown in Table 7.1. So, for this model the value of NOP is 1, the value of HWP is 0.8 and value of FMP is 0.1 (given in Table 7.1).

Table 7.1 Importance level of different learning techniques

Model	Author	Learning Techniques	Learning Problems	Performance factors	NOP	HWP	FMP
M1	Minaei et al. (2004)	K- nearest neighbour and genetic algorithm	CLS	Prediction accuracy	1	0.8	0.1
M2	Chih-Ming et al. (2006)	Item response theory	LPG	Concept relation degree	1	0.9	0.05
M3	Encheva et al. (2006)	Association rules	CLS	Peer review standard method	1	0.8	0.05
M4	Yang et al. (2008)	Data mining	OR	Pre-Post test analysis	1	0.8	0.15
M5	Liang et al. (2008)	Multi agent systems	LPG	Learner satisfaction degree	1	0.9	0.1
M6	Wang et al. (2009)	Decision tree and Data mining	POC	Teaching cost and pre-post analysis	1	0.6	0.125
M7	Norwai et al. (2009)	Decision tree and K means clustering	OR	Felder Index learning style	1	0.8	0.05
M8	Wang and Liao (2011)	ANN (Backpropagation algorithm)	CLP	Experimental and control test	1	0.6	0.125
M9	Van Seters et al. (2012)	Computer based adaptive learning environment	CLS	Correlation coefficient, accuracy	1	0.8	0.1
M10	Khamparia and Pandey (2015)	CBR, ANN and Data mining	LPG	Experimenatl analysis (Pre-Post)	1	0.9	0.15

The third and fourth column in the Table 7.1 shows learning techniques and ELP. Finally, the fifth, sixth and seventh column represents the NOP, HWP and FMP content respectively.

7.7.2 Comparative view of different Learning Problem Importance (LPI)

In this section, the learning problem importance (LPI) was computed using learning parameter importance (LPAI/SC) and Expert Cost (E).

LPAI is computed in three steps: In the first we have assigned the relative cost (RC) and relative importance (RI) to various learning parameters such as: Gender (G), Personality (P), Learning style (LS), Anxiety (AX), CoG style (CS), learner grade (LG), learner ability (LA), Motivation (MO), prior knowledge level (PKL) and learner interest (LI) with the help of domain experts. The RC and RI are shown in Column 2 and 3 of Table 7.2. Then the RC*RI is computed as shown in column 4 of Table 7.2.

Table 7.2 Computation of RC and RI

Learning parameter	RC	RI	RC*RI
Gender (G)	0.05	0.2	0.01
Personality (P)	0.3	0.9	0.27
Learning Style (LS)	0.2	0.6	0.12
Anxiety (AX)	0.3	0.7	0.21
Cognitive Style (CS)	0.4	0.8	0.32
Learner Grades (LG)	0.2	0.5	0.1
Learner Ability (LA)	0.3	0.5	0.15
Motivation (MO)	0.4	0.7	0.28
Prior Knowledge Level (PKL)	0.2	0.6	0.12
Learner Interest (LI)	0.2	0.8	0.16

In the next step, the total I of each model was computed. For example, model6 used learning parameters like G (0.01), P (0.27) and AX (0.21) as shown in the row headed by M6 in Table 7.2. Therefore, the total I for model6 was computed as (0.01 + 0.27 + 0.21 = 0.49) as shown in the last column of row headed by M6 in Table 7.2.

Table 7.3 Computation of LPI

Models	Gender	Personality	Learning Style	Anxiety	Cognitive Style	Learner Grades	Learner Ability	Motivation	Prior Knowledge level	Learner Interest	SC	E (SP+TEP)	LPI
M1						0.1					0.1	1.1	0.32
M2							0.15				0.15	1.6	0.46
M3									0.12	0.16	0.28	1.1	0.42
M4			0.12		0.32						0.44	1.1	0.51
M5					0.32		0.15			0.16	0.63	1.6	0.73
M6	0.01	0.27		0.21							0.49	0.8	0.46
M7			0.12						0.12		0.24	1.1	0.39
M8	0.01	0.27	0.12			0.1					0.5	0.7	0.44
M9	0.01							0.28	0.12		0.41	1.1	0.49
M10	0.01	0.27	0.12	0.21	0.32						0.93	1.6	0.9

The expert cost as shown in thirteenth column headed by E was computed by adding the expert survey cost (SP) (i.e cost of finding materials from journals or e-book or lecture videos, literature findings etc.) and teaching evaluation cost (TEP) (i.e the teaching cost and pre, post-test analysis cost, experimental and control group tests cost). The LPI (as shown in last column of Table 7.3) was computed using equation 7.1.

$LPI = W_{LPI} * (W_E * E + W_{SC} * SC)$ ------------------ (7.1)

Where W_E, W_{SC} and W_{LPI} are weight assigned by expert to E, SC and LPI respectively.

7.7.3 Comparative view of different learning technique complexity (LTCC)

Generally, the learning techniques consist of some proportion of algorithmic (A), mathematical (MA) and heuristic (HE) nature which affects its CC. Depending upon the technique the proportion of these nature may varies as High (H), Medium (M) and Low (L). This section described the calculation of complexity (CC) level of each technique as shown in Table 7.4. For ease of computation integer value 3, 2 and 1 are assigned to H, M and L respectively.

As shown in Table 7.4 the seventh column, resultant shows the mixed nature of technique.

It was calculated by taking the average of HE, A and MA proportion.

For eg, Model1,

H + M + L => (3 + 2 +1)/ 3 = 2 which was M (0.5).

For Model2,

M + M + L=> (2+ 2+ 1)/3=5/3= 1.5 approximately equal to 2, which was M(0.5).

For ease of computation H is assigned a value 0.8, M as 0.5 and L as 0.2.

Table 7.4 CC level of different learning techniques

Model	Author	Learning Techniques	HE	A	MA	Resultant	Assigned value
M1	Minaei et al. (2004)	K- nearest neighbour and genetic algorithm	H	M	L	M	0.5
M2	Chih-Ming et al. (2006)	Item response theory	M	M	L	M	0.5
M3	Encheva et al. (2006)	Association rules	L	M	M	L	0.5
M4	Yang et al. (2008)	Data mining	L	M	L	L	0.2
M5	Liang et al. (2008)	Multi agent systems	M	L	L	L	0.2
M6	Wang et al. (2009)	Decision tree and Data mining	L	M	L	L	0.2
M7	Norwai et al. (2009)	Decision tree and K means clustering	L	M	M	M	0.5
M8	Wang and Liao (2011)	ANN (Backpropagation algorithm)	L	H	H	M	0.5
M9	Van Seters et al. (2012)	Computer based adaptive learning environment	H	L	L	M	0.5
M10	Khamparia and Pandey (2015)	CBR, ANN and Data mining	L	H	H	M	0.5

The third column, in Table 7.4 represents learning techniques. The fourth, fifth and sixth column represents the HE, A and MA nature respectively. The computed average values obtained from fourth, fifth and sixth columns are shown by seventh column respectively. Column eight demonstrates the assignment of values based on resultant obtained levels.

7.7.4 Comparative view of different learning problems complexity (LPCC)

The complexity of learning problem depends upon its design (DC), time (TC) and space (SPC) complexity which is high (H), medium (M) or low (L). This section described the computation of CC level of each problem as shown in Table 7.5. For ease of computation integer value 3, 2 and 1 are assigned to H, M and L respectively. The overall CC of the model is shown in seventh column of Table 7.5. It is obtained by taking the average of CC of design, time and space. Like for M1, H + H + M => ceilof [(3 + 3 +2)/ 3] = 3 which will consider as H (0.8).

Table 7.5 CC level of different learning problems

Model	Author	Learning Problems	Design Complexity (DC)	Time Complexity (TC)	Space Complexity (SPC)	Overall Complexity	Assigned Value
M1	Minaei et al. (2004)	CLS	H	H	M	H	0.8
M2	Chih-Ming et al. (2006)	LPG	H	H	H	H	0.8
M3	Encheva et al. (2006)	CLS	H	H	M	H	0.8
M4	Yang et al. (2008)	OR	L	M	M	M	0.5
M5	Liang et al. (2008)	LPG	M	M	M	M	0.5
M6	Wang et al. (2009)	POC	M	M	M	M	0.5
M7	Norwai et al. (2009)	OR	L	L	M	L	0.2
M8	Wang and Liao (2011)	CLP	L	L	L	L	0.2
M9	Van Seters et al. (2012)	CLS	H	H	M	H	0.8
M10	Khamparia and Pandey (2015)	LPG	H	M	M	M	0.5

The column next to author contains the various learning problems. The fourth, fifth and sixth column contains the CC of DC, TC and SPC respectively. Seventh column represents the overall CC obtained by using average value of fourth, fifth and sixth column. Finally, a value has been assigned according to overall CC as shown in column eight.

7.7.5 Computation of I, CC and PI

I is computed as I = LPM + LPI; where LPM is Learning Problem Measurement

LPM = W_{LPM} * (W_{NOP} * NOP + W_{HWP} * HWP + W_{FMP} * FMP); Here W represents weight of No of Problems (NOP), Hierarchical Weight of Problem (HWP) and Factors Measuring Performance (FMP).

LPI is computed using equation 7.1 as shown in Table 7.3.

CC is computed as CC = LTCC + LPCC;

Where, LTCC is learning technique;

LTCC = W_{LTCC} * [Resultant of (HE + A + MA) /3];

LPCC = W_{LPCC} * [Resultant of (DC + TC + SPC) / 3];

Finally PI is computed using following formula:

$PI = I/CC = W_I * I / W_{CC} * CC$; here W_I is weight of overall importance and W_{CC} is weight of overall CC.

Table 7.6 Computation of I, CC and PI

Model	Author	LPM	LPI	I	LTCC	LPCC	CC	PI
M1	Minaei et al. (2004)	0.11	0.32	0.43	0.2	0.48	0.68	1.47
M2	Chih-Ming et al. (2006)	0.11	0.46	0.57	0.2	0.48	0.68	1.95
M3	Encheva et al. (2006)	0.1	0.42	0.52	0.2	0.48	0.68	1.78
M4	Yang et al. (2008)	0.11	0.51	0.62	0.08	0.3	0.38	3.8
M5	Liang et al. (2008)	0.12	0.73	0.85	0.28	0.3	0.58	3.41
M6	Wang et al. (2009)	0.12	0.46	0.58	0.28	0.3	0.58	2.33
M7	Norwai et al. (2009)	0.1	0.39	0.49	0.2	0.12	0.32	3.57
M8	Wang and Liao (2011)	0.09	0.44	0.53	0.2	0.12	0.32	3.86
M9	Van Seters et al. (2012)	0.11	0.49	0.6	0.2	0.48	0.68	2.05
M10	Khamparia and Pandey (2015)	0.12	0.9	1.02	0.2	0.3	0.5	4.76

In Table 7.6, third and fourth column contains the computed value of LPM and LPI respectively. The values in fifth column were obtained by combining the values of third and fourth column. Sixth and seventh column contains the value of LTCC and LPCC respectively. The value in eighth column was obtained by combining the results of sixth and seventh column. The values in ninth column (PI) were computed using fifth (I) and eight (CC) columns.

Calculation I and CC for Model M1 (Minaei et al. 2004)

I comprised of LPM and LPI. The LPM was obtained from combination of No of Problems (NOP), Hierarchical Weight of Problem (HWP) and Factors Measuring Performance (FMP).

Similarly, LPI comprised of Expert importance (ExIm) and Student learning characteristics (SC). The E categorized into Survey pay (SP) and Teaching evaluation pay (TEP). The SC for model M1 is: learner grades.

$I = LPM + LPI$ -- (7.2)

$LPM = W_{LPM} * (W_{NOP} * NOP + W_{HWP} * HWP + W_{FMP} * FMP)$

$LPM = 0.2 * (0.2 * NOP + 0.4 * HWP + 0.4 * FMP)$ --------- (7.3)

For model M1, NOP was 1 as there was only one ELP preferred by model. HWP depends on the inclusion of one problem in another, as the ELP applicable for model M1 is CLS so its rank is 0.8 and FMP depends on the performance measure involved for model i.e. prediction accuracy for M1 whose importance assigned is 0.1 as shown in Table 7.1.

So, equation 6.2 modified as LPM = 0.2 * (0.2 * 1 + 0.4 * 0.8 + 0.4 * 0.1) = 0.11

$LPI = W_{LPI} * (W_E * E + W_S * SC)$

LPI = 0.8 * (0.3 * (SP+TEP) + 0.7 * SC) ------------- (7.4)

Every student characteristics computed on basis of RC and RI. Every individual learning characteristic of student is governed by RC*RI = SC.

As for Model M1, only learner grade is considered as student characteristic.

For this, the SC = (0.2*0.5) = 0.1.

Now, equation 7.3 get modified as

LPI = 0.8 * (0.3 * (0.6+0.5) + 0.7 * 0.1) = 0.32.

Total computed I value is I = 0.11 + 0.32 = 0.43

The CC comprised of LTCC and LPCC.

CC = LTCC + LPCC -------- (7.5)

Computation of LTCC

$LTCC = W_{LTCC}$ * [Resultant of (HE+ A + MA) / 3]

LTCC = 0.4 * [Resultant of (3 + 2 + 1)/3] = 0.4 * 2, here 2 denotes M ----------------- (7.6)

Based on expert suggestions HE, A and MA factors were computed on the basis of their predefined level values which was for High as (H: 3), Medium as (M: 2) and low as (L: 1).

For model M1, HE value was High, A was Medium and MA was Low. The above representation (x: y) determines x: learning technique and y: value level as High, Medium and Low. The resultant value was obtained by taking the average of predefined value assigned to individual learning techniques.

Like for M1, average of values of (H, M, L) => (3 + 2 +1)/ 3 = 2, 2 denotes M and the value of M was 0.5.

From expert suggestion we have assigned the values 0.8, 0.5 and 0.2 to the resultant H, M and L.

So, equation 7.6 will be written as: LTCC = 0.4 * 0.5 = 0.2.

Computation of LPCC

$LPCC = W_{LPCC}$ * [Resultant of (DC + TC + SPC) / 3] ---------------------- (7.6)

The LPCC was computed from the values of design complexity (DC), time complexity (TC) and space complexity (SPC).

For model M1, the complexity of DC was High, the complexity of TC was High and the complexity of SPC was Medium. The above representation (x: y) determines x: learning problem complexity factors and y: value level as High, medium and low.

Like for M1, Average of (H + H + M) => (3 + 3 +2)/ 3 = ceilof (2.6) = 3, 3 means H and the expert has assigned value 0.8 to H.

So, from equation 7.7 LPCC = 0.6 * 0.8 = 0.48.

Final CC = LTCC + LPCC = 0.2 + 0.48 = 0.6

Computation of PI

$PI = I/CC = W_I * I / W_{CC} * CC = (0.7 * 0.43) / (0.68*0.3) = 1.47$

Similarly, the PI of different models was calculated. The PI for M2, M3, M4, M5, M6, M7, M8, M9 and M10 were 1.95, 1.98, 1.78, 3.8, 3.41, 2.33, 3.57, 3.86, 2.05 and 4.76 respectively.

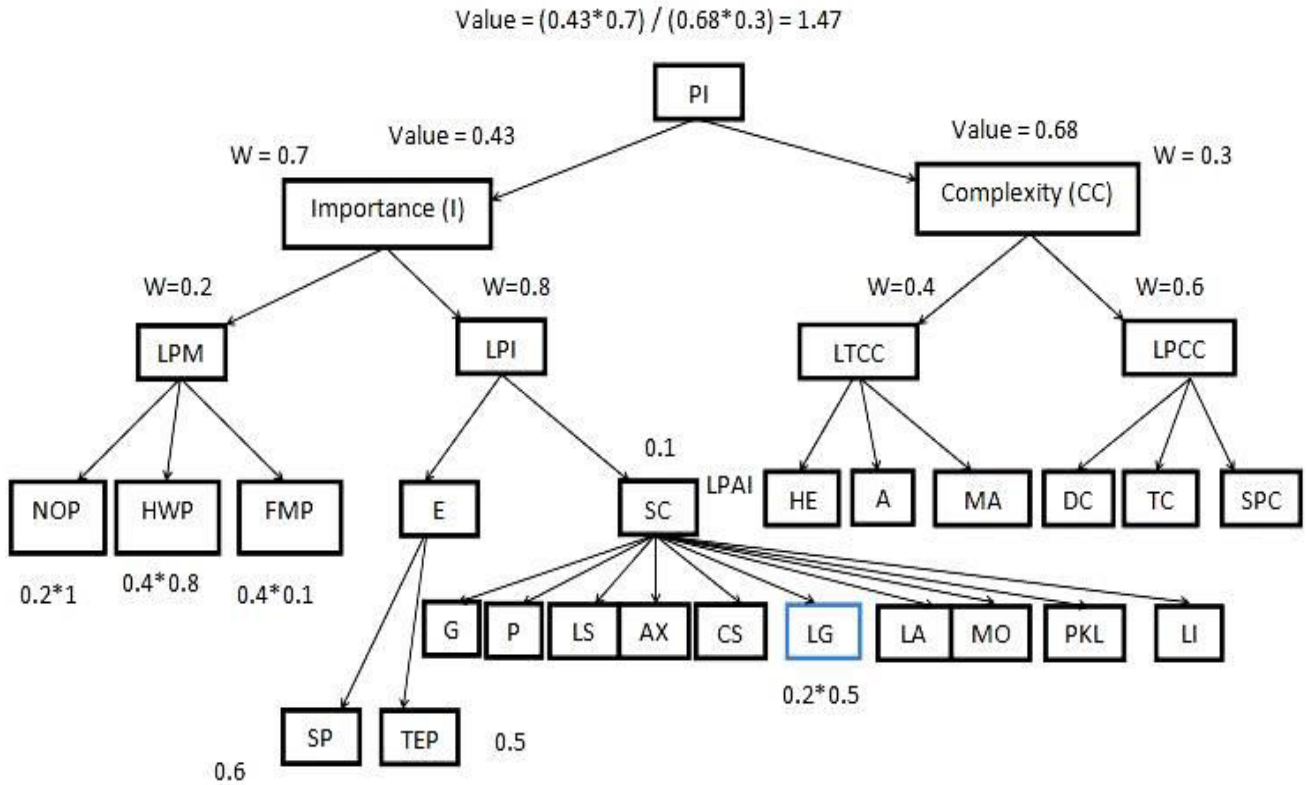


Figure 7.10 Hierarchical representation of PI

7.8 Results and discussion

With the help of domain expert different weights 0.7 and 0.3 were assigned to Importance and Complexity (CC) respectively. The PI was calculated as follows:

PI = W_I * I of learning technique and problem / W_{CC} * CC of learning technique and problems.

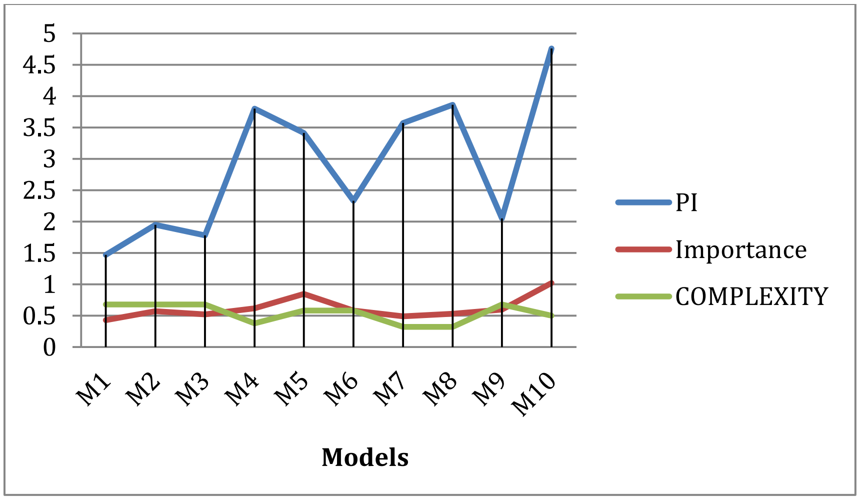


Figure 7.11 Comparative views of PI, I and CC of different models

From Figure 7.11 it has been observed that Model10 (1.02) and Model1 (0.43) has highest and lowest values of I of student characteristics. The Importance of Model2, Model3, Model4, Model5, Model6, Model7, Model8 and Model9 are 0.57, 0.52, 0.62, 0.85, 0.58, 0.49, 0.53 and 0.6 respectively which remains between 0.1-1.0. The values provided in brackets are I which is obtained using combination of learning techniques and learning problems.

Model7 (0.32) and Model8 (0.32) has lowest CC among all models. Model4 and Model10 have CC of 0.38 and 0.5 respectively. Model5 and Model6 has equal CC i.e. 0.58 and Model1, Model2, Model3 and Model9 have equal CC value of 0.68.

It is observed from Figure 7.11, Model10 and Model1 has highest and lowest PI value i.e. 4.76 and 1.36 respectively. Model2 (1.95), Model3 (1.78), Model9 (2.05), Model6 (2.33) have PI which lie in interval 1.5 – 2.5. Model4 (3.8), Model8 (3.86), Model5 (3.41) and Model7 (3.57) have PI values which lies in interval 3.0-4.0.

7.9 Conclusion

In first aspect, we have made illustration of various concepts pertaining to two points of view computational and E-learning. From computational point of view, we have introduced: data mining methods such as Decision tree, Hierarchical and Non-Hierarchical clustering, and Artificial neural networks; Hidden Markov Model and its characteristics, and Petri net modeling.

From the E-learning point of view we have presented E-learning with its advantages and standards, learning theory and approaches, learning strategy, and performance evaluation. For selection of different semantic web-based services variety of qualitative and CoG parameters were used to deal with uncertainty which relied on proposed rule-based model approach.

The rule base model generated from the hierarchal structure is used for computing CCF of each qualitative and QUANT parameter. The generated rule base is dependent on structural arrangement of hierarchical tree which perform changes as rule-based changes. The proposed CoG based model delivers very low computational overhead which enables efficient, effective and smarter selection of services required for delivery to different agents. The proposed approach overcomes limitations of different models by combining several CoG parameters, focusing on user's preferences on QoS attributes in an efficient way. The intended illustrated example demonstrates that uncertainty dependent model provides enough flexibility to consumer or agent so that they can select and consume best service which suited and delivers according to their needs and requirement. From the next chapter, the research work performed in the thesis will be presented.

In the second aspect, e-learning system performance is computed as complexity and importance with consideration of students learning features, intelligent computing methods and adoption of e-learning problems. The performance measure of system also depends on number and type of problems, weight factors from expert consultancy also being considered. Further, the different types of complexities with respect to several models being observed and provides the computational complexity in term of High (H), Medium (M) and Low (L).Individual learner's features have used to compute cost and learner problem importance which is assigned corresponding to every model. The importance and complexity are used for computation of performance index corresponding to every model.

For every model, PI is computed with help of importance and complexity and represented with different graphs. The proposed model which involves different learning parameters like G, P, A, L and C which uses computation techniques like CBR, ANN and DM achieve highest performance index in comparison to other models.

The proposed study evaluated different e-learning systems which involves different ELP and techniques and enhance efficiency of particular proposed system which incorporates several student features. The weights used in proposed work is subjective which are assigned on consultation with experts which become limitation for proposed study work and could be removed in future by using advanced weight assessment methods.

Chapter 8

Conclusions

In this thesis, efforts have been made to provide more efficient approaches for personalization of learning content as per learner needs, classification and categorization of learning content, enhance productivity of learner by considering psychological factors, designing of threat driven framework to remove vulnerabilities present in E-learning system using petri nets and perform performance evaluation of all methods to provide suitable content to learner in web enabled system. Integrated approach of data mining and ANN methods are used for classification and categorization of learning content. ANN methods help in categorization and prediction of student features on basis of their performance. A novel feature of case based reasoning is involved to represent the attribute value pairs of student features as cases in case base. HMM and petri net based systems has been used to deliver an adaptive material according to psychological and environmental factors and petri net mitigate the threats present in E-learning system by using software metrics simultaneously. Finally, the performance evaluation performed by E-learning systems on the basis of learning techniques and learning methods. This chapter is organized as follows: section 8.1 deals with the concluding remarks summarizing the main work of each chapter. Section 8.2 describes the main contribution of the thesis and scope of future work has been described in 8.3.

8.1 Concluding Remark

A literature review of some reported works on E-learning in four main directions namely: Intelligent soft computing techniques in E-learning, Semantic web, Ontology, web services and E-learning, Hidden Markov Model paradigm for E-learning and Petri Net modeling based system for E-learning has been presented in chapter 1. Chapter 1 also presents the motivations, objectives and plan of the thesis. The survey of research works in chapter 1 shows that this is a highly powerful and attractive area of research nowadays.

An introduction to the very basic concepts which pertain to various intelligent computing methods used in the thesis such as Data mining, Case Based Reasoning and ANN methods (Decision tree, Neural networks, Cases), Hidden Markov Model (HMM) with its application and usage in E-learning systems, Petri nets and their usages in security based e-learning system, and Semantic web technology with ontology and web services, E-learning, Learning theory, Learning strategy and evaluation of learner's performance have been given in Chapter 2.

Chapter 3 presents an adaptive CBR-ANN-DM based integrated method to provide learning material to student according to their needs at different levels of programming in computer science. This method has been deployed for the learning of C Programming language. This chapter describes the use of data mining and ANN methods for classification and categorization of learning content. ANN methods help in categorization and prediction of student features on basis of their performance. A novel feature of case based reasoning is involved to represent the attribute value pairs of student features as cases in case base.

The evaluation of the presented integrated methods has been performed using experimental sample comprised of pre and post-test methods and following conclusion have been made:

- On the basis of different abilities of students like Gender, Anxiety, Personality, Learning and cognitive level the proposed system provides learning materials of different difficulty levels to learners for improvement of their syntax, logical and application-oriented abilities. After comparison analysis it has been found that none of the researchers considered G, P, A, L and C ability features for providing the path sequencing in C programming course.

- Experimental analysis has been performed for checking feasibility of proposed system by dividing student into experimental and control groups. Experimental group has C programming-based course, post-test demonstrated that in Syntax, Logical and Application feasibility portion of post-test, the score obtained by experimental group is higher than score obtained by control group in term of mean score comparison. It means C Programming CBR based e-learning system is better than regular learning course and delivers the material as per learner abilities. Our method has been compared with other existing works and it has been found that our method provides more effective results.

Chapter 4 presents a Hidden Markov Model based E-learning system which describes its two common perspectives: To develop an adaptive web based educational system using HMM for computer programming. In the proposed approach an adaptive web based e-learning system based on HMM approach which predicts the future actions and next lecture content of C programming to be visited by student based on history of lecture contents and delivers the learning material according to their ability and preferences. There are mainly three phases exists in web based system. In starting phase, for every students a HMM (λ) is built based on their previous lecture content access sequence, Baum Welch algorithm has been used in intermediate phase to adjust the starting HMM (λ) and to maximize the new lecture path sequence also known as observed sequences. In the final phase, probability $\alpha_t(i)$ of each lecture content can be denoted as states for programming course is determined by forward algorithm. After computation, maximum value will determine the next future action or lecture content to be visited by students.

In the evaluation of presented learning strategy the following conclusions have been made:

- An experiment performed to evaluate the learning strategy, different cases have been presented with different performance and behaviour.
- The proposed HMM based learning system has been compared with Multilayer perceptron network to predict the student actions and their progress in programming in coming months. The input of network is student actions. It has been tested with record of 50 students data and evaluated with 25 data and performance rate achieved was 78.15

compared to HMM i.e. 80.23 which show that our HMM based approach is more effective in terms of performance.

Chapter 5 presents an adaptive system to improve the learning performance of learners by predicting their psychological and environmental factors and enhance their learning productivity In addition to other HMM related model, grade prediction of learner based on their P and E factors have been used which focuses on improvement of learner performance by providing positive factors of complimentary nature with aid to negative factors. The proposed work has been categorized into three steps: deployment of HMM model to improve the performance of learner by observing the impact of Hidden Markov Model which relies on psychological and environmental factors and mapping has been performed to balance these factors by introducing their complimentary factors which reduces negative behavior and induces more better and accurate results.

The training for Hidden Markov Model has been performed by initializing various probabilities matrix as transition (A), observation (B) and initial state distribution (π). The performance of Hidden Markov Model depends on these transition systems which initialize the parameter values by considering the forward and backward algorithm which involves hidden states and unobserved state sequences.

The following conclusions have been made:

- For HMM verification and performance feasibility different logical combinations of states being considered in which best state would validate the suitability of particular observation sequence. With the help of HMM model the total number of computations is reduced at great extent and with help of it we predict the grade at intermediatary stage also which is not possible by any other prediction models. This shows that HMM can be used efficiently in the field of e-learning to enhance the learning curve of learners.

Chapter 6 presents a threat driven security framework using petri nets to remove the design vulnerabilities in system. The completeness and soundness of Aspect oriented stochastic petri nets models could be measured by proposed modified threat driven framework. Varieties of threat modeling phases like assessment of risk, mitigation assessment, attenuation description were added to proposed modeling framework which enhance efficiency and accuracy of proposed model. The risk introduced in analysis phase measured by computing the occurrence of threats and their related impacts which are induced in system. The three behavioral properties of petri nets like boundness, reachability and liveness responsible for measuring overall correction assessment of proposed system.

The following conclusions have been made:

- The proposed aspect oriented stochastic petri net based framework consist of six modules: Disintegrate application, Disintegration correction assessment, Threat identification, Identify application vulnerability, Risk assessment matrix, Mitigate (Attenuate) threats, Mitigation (Attenuation) correction assessment and Mitigation (Attenuation) assessment which compute the security metrics in term of base, temporal and environmental metrics.
- The framework has been evaluated by using a security metric approach and it is found that all the criteria mentioned in the evaluation approach are satisfied by the framework.
- The framework has been evaluated by Risk assessment and threat matrix which is used to identify the vulnerable places in E-learning system and mitigate those threats.
- An experiment performed on the model before and after applying mitigation for threat removal. It has been observed that after applying threat mitigations when security metric is computed it come down to 2.3 from 4.3 before applying mitigations.
- A comparative analysis has been done of modified proposed threat modeling framework with other systems and it has been found that proposed framework is more efficient as it includes all kind of security metrics i.e. base, temporal and environmental.

8.2 Main contribution

The thesis mainly presented the adaptive CBR-ANN-DM based integrated method to provide learning material to student according to their needs at different levels of programming in computer science; an adaptive web based educational system using HMM for computer programming and to improve the learning performance of learners by predicting their psychological and environmental factors and enhance their learning productivity; threat driven security framework using petri nets to remove the design vulnerabilities in system; and performance evaluation of E-learning system on the basis of learning problem, techniques importance and complexity. The main contribution of the thesis as follows:

- A review of the reported research work on E-learning has been performed. From the performed review, some important issues have been identified and observations have been taken.
- Intelligent soft computing methods have been integrated to provide learning material to student according to their needs at different levels of programming in computer science. This model firstly collect the data based on student features, then ANN model is used to find the relationship between student features and learning performance. Now, data mining technique is used for classification of student features. Finally, case based reasoning is involved to represent the attribute value pairs of student features as cases in case base.
- A HMM model of learning has been developed in which data is collected from adaptive e-learning system and action of each student has been gathered according to every lecture topic which they visited based on history of concepts. Baum-Welch algorithm has been used to predict the student future behaviour and navigation actions within an e-learning system. Similarly grade prediction of learner has been done on basis of sequence of their psychological and environmental factors.
- Threat driven security framework involving usage of stochastic petri nets has been proposed to remove the design vulnerabilities in system. The completeness and soundness of Aspect oriented stochastic petri nets models could be measured by proposed modified threat driven framework. Varieties of threat modeling phases like assessment of risk, mitigation assessment, attenuation description were added to proposed modeling framework which enhance efficiency and accuracy of proposed model. Threat mitigation is entirely dependent on value of security metrics which is computed on basis of base, temporal and environmental metrics.
- The performance of e-learning system which involves student features, techniques and important learning problems could be evaluated and represented in term of complexity and parameters importance. The estimated weight and other factors are responsible for analyzing the performance of e-learning problems which embarked system accuracy. For

every model, design, time and space complexity leads to determination of level of complexity. This has not done by other researcher in the area.

8.3 Future works

Future work can be carried out in the field of E-Learning and M-Learning. The field of E-learning and M-Learning is still growing day by day and there are wide opportunities for future research in order to enhance the learning process.

- In adaptive E-learning system we have considered CBR-DM-ANN method. In future reduction of rule set could be achieved by deploying Bayesian governed neuro symbolic rules where size of data mining governed rules is larger. In proposed work we have incorporated only limiting features of programming otherwise computational overhead will burden different problem-solving capabilities related to algorithmic complexities etc. Variety of programming aspects supported with different learning styles has been included in described study work.
- In HMM based learning model the learning performance of learner is always going to be degraded if sequence of two negative factors are provided to solve problem. The implementation of HMM system may be extended in such a way that such drawbacks have been reduced and more efficient and personalized services will be provided to learners.
- The use of Semantic description, Hybrid and Ensemble learning methods in the E-learning could be used in future to enhance performance evaluation process since it is an important and useful process in E-learning environment. Also integrating advanced features of learning styles in adaptive learning also enhances the evaluating power of different attributes in predicting different learning styles. These techniques help to improve the efficiency and performance of classification models.

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List of Publications

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1. Aditya Khamparia, Babita Pandey.: Knowledge and Intelligent Computing Methods in e-learning. In: International Journal of Technology Enhanced Learning, **Inderscience [SCOPUS Indexed, ACM Digital Library] Vol. 7, issue 3, pp. 221-242, (2015).**

2. Aditya Khamparia, Babita Pandey.: Threat driven modelling framework using petri nets for e-learning system. In: **Springer Plus (SCI-E, Thomson Reuters) Vol. 5, issue 1, pp. 446-450, (2016).**

3. Aditya Khamparia, Babita Pandey.: Effects of Visual Map Embedded Approach on Students Learning Performance using Briggs Meyer Learning Style in Word Puzzle Gaming Course. In: **Computers and Electrical Engineering, Elsevier (SCI-E, Thomson Reuters), 2018.**

4. Aditya Khamparia, Babita Pandey.: A Novel Method of Case Representation and Retrieval in CBR for e-learning. In: **Education and Information Technologies (Springer) (SCOPUS Indexed, ACM, and DOAJ) Vol. 22, issue 1, pp. 337-354, (2015).**

5. Aditya Khamparia, Babita Pandey.: A QoS and Cognitive parameter based uncertainty model for selection of semantic web services. In: **Indian Journal of Science and Technology (SCOPUS) Vol. 9, issue 44 (2016).**

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14. Aditya Khamparia, Babita Pandey.: Prediction of Combination of Balanced Amount of Positive and Negative Factor to Improve the Learner’s Performance using HMM. In: Journal of Computers in Education **(Springer) [Paper Communicated, Under Review].**

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25. Aditya Khamparia, Babita Pandey.: Adaptive E-learning based Udutu System for Object Oriented Programming. In: International Journal of Applied Engineering Research (IJAER) **[Scopus Indexed] .**

Appendices

Control Group

Student ID	Pre-Test Analysis						Post-Test Analysis					
	Total marks (100)			Marks Proration Total marks (160)			Total marks (100)			Marks Proration Total marks (160)		
	Pre-test (SY out of 30)	Pre-test (LG out of 30)	Pre-test (AP out of 40)	Pre-test (SY out of 60)	Pre-test (LG out of 60)	Pre-test (AP out of 40)	Post-test (SY out of 30)	Post-test (LG out of 30)	Post-test (AP out of 40)	Post-test (SY out of 60)	Post-test (LG out of 60)	Post-test (AP out of 40)
RGID1	18	14	13	36	28	13	13	14	14	26	28	14
RGID2	21	19	8	42	38	8	26	19	7	52	38	7
RGID3	10	14	10	20	28	10	5	15	12	10	30	12
RGID4	15	12	15	30	24	15	3	12	15	6	24	15
RGID5	9	12	10	18	24	10	12	10	12	24	20	12
RGID6	21	17	25	42	34	25	25	17	21	50	34	21
RGID7	15	20	12	30	40	12	15	19	15	30	38	15
RGID8	8	10	14	16	20	14	12	10	16	24	20	16
RGID9	20	22	25	40	44	25	14	22	26	28	44	26
RGID10	5	8	9	10	16	9	10	8	12	20	16	12
RGID11	24	24	24	48	48	24	27	24	22	54	48	22
RGID12	15	24	11	30	48	11	13	22	12	26	44	12
RGID13	4	2	7	8	4	7	9	1	9	18	2	9
RGID14	13	13	18	26	26	18	4	13	14	8	26	14
RGID15	8	10	9	16	20	9	4	12	12	8	24	12
RGID16	6	7	11	12	14	11	12	7	11	24	14	11
RGID17	8	5	14	16	10	14	9	5	13	18	10	13
RGID18	1	2	1	2	4	1	0	2	2	0	4	2
RGID19	21	18	31	42	36	31	16	18	24	32	36	24
RGID20	20	17	25	40	34	25	20	19	23	40	38	23
RGID21	1	1	2	2	2	2	3	2	2	6	4	2
RGID22	13	17	14	26	34	14	19	15	12	38	30	12
RGID23	12	12	16	24	24	16	18	14	19	36	28	19
RGID24	4	7	4	8	14	4	19	8	2	38	16	2
RGID25	12	8	25	24	16	25	15	9	22	30	18	22
RGID26	12	11	19	24	22	19	15	12	17	30	24	17
RGID27	18	14	12	36	28	12	25	14	18	50	28	18
RGID28	18	13	27	36	26	27	19	13	29	38	26	29
RGID29	5	6	9	10	12	9	8	7	12	16	14	12
RGID30	9	8	13	18	16	13	18	8	19	36	16	19
RGID31	8	7	12	16	14	12	12	7	17	24	14	17
RGID32	11	11	15	22	22	15	14	13	15	28	26	15
RGID33	3	5	3	6	10	3	12	6	8	24	12	8
RGID34	12	8	20	24	16	20	15	8	22	30	16	22
RGID35	10	9	15	20	18	15	11	9	17	22	18	17
RGID36	13	14	16	26	28	16	12	14	15	24	28	15
RGID37	6	5	14	12	10	14	7	4	17	14	8	17
RGID38	21	18	19	42	36	19	26	18	19	52	36	19
RGID39	24	23	32	48	46	32	23	23	36	46	46	36
RGID40	17	15	25	34	30	25	24	15	28	48	30	28
RGID41	11	16	10	22	32	10	18	16	19	36	32	19
RGID42	8	4	18	16	8	18	6	5	18	12	10	18
RGID43	10	6	18	20	12	18	19	6	21	38	12	21
RGID44	9	12	6	18	24	6	13	12	9	26	24	9
RGID45	7	14	10	14	28	10	14	14	12	28	28	12
RGID46	4	2	8	8	4	8	10	2	13	20	4	13
RGID47	1	1	2	2	2	2	6	1	8	12	2	8
RGID48	14	18	14	28	36	14	7	18	18	14	36	18
RGID49	21	20	24	42	40	24	26	21	21	52	42	21
RGID50	19	15	22	38	30	22	18	17	20	36	34	20

Experimental Group

Student ID	Pre-Test Analysis						Post-Test Analysis					
	Total marks (100)			Marks Proration Total marks (160)			Total marks (100)			Marks Proration Total marks (160)		
	Pre-test (SY out of 30)	Pre-test (LG out of 30)	Pre-test (AP out of 40)	Pre-test (SY out of 60)	Pre-test (LG out of 60)	Pre-test (AP out of 40)	Post-test (SY out of 30)	Post-test (LG out of 30)	Post-test (AP out of 40)	Post-test (SY out of 60)	Post-test (LG out of 60)	Post-test (AP out of 40)
UGID1	10.5	12	13	21	24	13	15	15	22	30	30	13
UGID2	13.5	14	18	27	28	18	22	16	24	44	32	18
UGID3	16	13	13	32	26	13	19	17	18	38	34	13
UGID4	20.5	10	19	41	20	19	19	12	28	38	24	19
UGID5	10	13	12	20	26	12	14	11	24	28	22	12
UGID6	17	16	18	34	32	18	18	19	26	36	38	18
UGID7	14	8	16	28	16	16	16	12	29	32	24	16
UGID8	20.5	18	22	41	36	22	22	20	34	44	40	22
UGID9	6	17	16	12	34	16	14	18	28	28	36	16
UGID10	22	18	19	44	36	19	13	22	30	26	44	19
UGID11	5	5	7	10	10	7	10	14	16	20	28	7
UGID12	20.5	22.5	19.5	41	45	19.5	22	24.5	34.5	44	49	19.5
UGID13	0	5.5	4.5	0	11	4.5	8	7.5	12.5	16	15	4.5
UGID14	17	10.5	14.5	34	21	14.5	16.5	13.5	22.5	33	27	14.5
UGID15	8.5	9.5	14	17	19	14	14	14.5	19	28	29	14
UGID16	19.5	8	14	39	16	14	21.5	11.5	28	43	23	14
UGID17	27.5	9.5	22	55	19	22	27	13.5	26	54	27	22
UGID18	19.5	21.5	21	39	43	21	21	23	29	42	46	21
UGID19	0	5	0	0	10	0	5.5	8	6	11	16	0
UGID20	18.5	16	17.5	37	32	17.5	20.5	20	27	41	40	17.5
UGID21	20.5	15.5	19	41	31	19	23.5	17	24	47	34	19
UGID22	17	16	18.5	34	32	18.5	18	18	26	36	36	18.5
UGID23	0	2.5	5.5	0	5	5.5	8	9	12	16	18	5.5
UGID24	4	3	9	8	6	9	13	6	14	26	12	9
UGID25	5	9	12.5	10	18	12.5	13	13	16	26	26	12.5
UGID26	5	8	10	10	16	10	8	16	16	16	32	10
UGID27	5.5	9	17	11	18	17	17	12	26	34	24	17
UGID28	4.5	8	8	9	16	8	12	10	12	24	20	8
UGID29	9.5	10	18	19	20	18	18	14	28	36	28	18
UGID30	6	18	15.5	12	36	15.5	12	20	26	24	40	15.5
UGID31	11	21	0	22	42	0	16	25	10	32	50	0
UGID32	12.5	15	16.5	25	30	16.5	16	19	24	32	38	16.5
UGID33	8.5	7.5	14.5	17	15	14.5	19	14	23.5	38	28	14.5
UGID34	0	0	8	0	0	8	8	5	12.5	16	10	8
UGID35	15.5	16.5	16	31	33	16	20	18.5	29	40	37	16
UGID36	23	22	21	46	44	21	26	24	33	52	48	21
UGID37	0	0	0	0	0	0	8	6	9	16	12	0
UGID38	0	5	8	0	10	8	0	8	12	0	16	8
UGID39	3.5	6	12	7	12	12	17	10	20	34	20	12
UGID40	18.5	18	16.5	37	36	16.5	24	19	24	48	38	16.5
UGID41	20	20	22.5	40	40	22.5	23	20	32	46	40	22.5
UGID42	0	0	0	0	0	0	14	9	8	28	18	0
UGID43	16.5	26.5	25.5	33	53	25.5	18	24.5	32	36	49	25.5
UGID44	7.5	12.5	16.5	15	25	16.5	17	16	24	34	32	16.5
UGID45	3	5	14	6	10	14	14	8.5	20.5	28	17	14
UGID46	10.5	14.5	15	21	29	15	15	18	25	30	36	15
UGID47	23.5	21	20.5	47	42	20.5	24	25	23	48	50	20.5
UGID48	8	6	13	16	12	13	13	10	18	26	20	13
UGID49	16	10	15	32	20	15	18	15	23	36	30	15
UGID50	8	7	14.5	16	14	14.5	17	12	24	34	24	14.5

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