

Existing Learning Management Systems (LMS) miss-out the important roles of Instructional design (ID) models for qualitative lessons that could guarantee learning. This is because contemporary LMS provide a mere plane and passive platform for content authoring, thus becomes vulnerable for poor instructional design. This work demonstrates an effort to ameliorate this limitation by extending the IEEE Learning Technology System Architecture (LTSA) with ID design processes. A neuro-fuzzy model of learners' traces on the platform is used to evaluate the extended architecture.

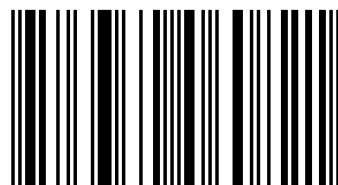


Rafiu Mope Isiaka

A Neuro-Fuzzy Model for E-Learning Activities



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DEDICATION

To all great minds.

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I humbly wish to appreciate the management and entire staff of Ladoke Akintola University of Technology (LAUTECH), Ogbomosho for creating and maintaining a good platform for academic excellence. I wish to specifically thank my supervisors Prof. E.O. Omidiora, Prof. S.O.Olabiyisi and Dr. O.O. Okediran for their guidance and for being role models in the profession. I am highly indebted to Dr. Mrs. A.B. Adetunji (HOD), Prof. O.J. Emuoyibofarhe, Dr. R.A. Ganiyu, Dr. O.T. Arulogun and all my internal and external assessors. You are all paragon of excellence, your contributions and suggestions greatly enrich the quality of this work. I wish to appreciate the Proprietor of IQRA College, Ilorin – Alhaji Aliu Badmus for believing in my capabilities. Forever I would be grateful to the management of Kwara State University, (KWASU), Malete, all staff and students of the Department of Computer, Library and Information Science, my family, friends and well wishers for their supports and encouragements. Ultimately, to my Lord, God, the Almighty, I submissively say thank you.

ABSTRACT

E-learning system is an Information Technology-based platform adopted globally to complement or supplement the traditional mode of education. Most existing works on e-learning system conceptualized on Learning Technology System Architecture (LTSA) standard for content adaptability and interoperability but played less on instructional design theory and dynamic learners' activities monitoring. This study therefore extends LTSA with Instructional Design (ID) subsystem and a neuro-fuzzy artificial intelligence model for automatic interpretation of learners' activities.

The learning resource store in the LTSA was extended with a process for five selected instructional design theories (Gagnes, Dick and Carey, ADDIES, Merrills and Kemp). The extended LTSA was implemented on open-sourced Modular Object Oriented Distance Learning Environment (Moodle). The Students' Impression (SI) on the extended LTSA was investigated through Survey Monkey online platform using sixty (60) 300 level, B.Sc Computer Science students that offered System Analysis and Design (CSC 306) during the 2013/2014 session at Kwara State University, Malete as a case study. The effectiveness of the extended LTSA for the students under consideration was determined on the basis of mean score of the class examination grades. Furthermore, the evaluation process in the LTSA was extended to include diagnostic process, after which a six layer feed-forward neuro-fuzzy network model for learners' activities was developed and integrated. The developed neuro-fuzzy model was simulated in Matrix Laboratory editor. The performance of the developed model was evaluated by comparing the developed model with the existing Mamdani Fuzzy, Sugeno Fuzzy and Sigmoid neuro-fuzzy learner' activities models in

terms of Mean Absolute Error (MAE) and Root Mean-Squared Error (RMSE). The complexity of the developed model was determined on the basis of accuracy, True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN).

The effect of the extended LTSA on the academic performance of the students yielded 56.98 class mean score. The MAE and RMSE obtained for the developed model are 127.4 and 11.3 respectively while those of Mamdani Fuzzy are 420.9 and 20.6 respectively. Also, these values for Sugeno Fuzzy are 2190.5 and 46.9 respectively while those of Sigmoid neuro-fuzzy are 157.6 and 12.6 respectively. Furthermore, complexity of the developed model assumed an accuracy value of 0.9, TP value of 67.0, FP value of 9.0, TN value of 74.0 and FN of 0.0. The Triangle model which shares the same accuracy value of 0.9 with the developed model has TP value of 66.0, FP value of 18.0, TN value of 65.0 and FN of 1.0.

Consequently, the integrated ID-subsystem facilitates grounded instruction development that provides improved academic performance for the class. Also, the developed neuro-fuzzy model which outperformed the other three models on the complexity metrics offers seamless evaluation of learners' activities.

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LIST OF ACRONYMS

- i. ACE - Adaptive Coach for Exploration
- ii. ADDIES - Analyze, Design, Development, Implement, and Evaluate
- iii. ADL - Advanced Distributed Learning Initiative
- iv. ADLNet: Advanced Distributed Learning Network
- v. AEH - Adaptive Educational Hypermedia
- vi. AES - Adaptive E-learning System
- vii. AHAM - Adaptive Hypermedia Authoring Mode
- viii. AI - Artificial Intelligence

- ix. AICC - Aviation Industry CBT (Computer-Based Training) Committee
- x. AIS - Artificial Immune System
- xi. ANFIS - Adaptive Network based Fuzzy Inference System
- xii. ANN - Artificial Neural Networks
- xiii. ARIADNE - Association of Remote Instructional Authoring and Distribution Networks for Europe
- xiv. CAM - Content Aggregation Model
- xv. CE - Curriculum Elements
- xvi. CEN - Centre de European Normalisation
- xvii. CMC - Computer Mediated Communication

- xviii. COA - Centroid of Area
- xix. COG - Centre of Gravity
- xx. COM - Center of Maxima
- xxi. COS - Centre of Sum
- xxii. CSCLAMS - Computer Science Learning Activities Management System

- xxiii. DBMS - Database Management Systems
- xxiv. DCMI - Dublin Core Metadata Initiative
- xxv. DoD - Department of Defense
- xxvi. E-learning – Electronic Learning
- xxvii. FIS - Fuzzy Inference System
- xxviii. FSLSM - The Felder Sliverman Learning Style Model
- xxix. GEM - Gateway of Educational Materials
- xxx. GOFAI - Good-Old-Fashioned-AI
- xxxi. GUI- Graphical Users Interface
- xxxii. HTML – HyperText Markup Language
- xxxiii. ICT - Information and Communication Technology
- xxxiv. ID - Instructional Design
- xxxv. IEEE - Institute of Electrical and Electronic Engineering
- xxxvi. IES - Intelligent Educational System
- xxxvii. IMS- Instructional Management Systems Global Learning Consortium
- xxxviii. ISD - Instructional System Design
- xxxix. ISO - International Standards Organization
 - xl. ISP – Internet Service Provider
 - xli. ISSS - Information Society Standardisation System,
 - xlii. IT - Information Technology
 - xliii. ITS - Intelligent Tutoring Systems
 - xliv. KWASUNET – Kwara State University Networks
 - xlvi. LAOS - Layered Adaptive hypermedia authoring model and its algebraic OperatorS
 - xlvi. LD - Learning Design

- xlvi. LDMS - Learning Design Management System
- xlvi. LDPA - Learning Design and Packaging Architecture
- xlix. LMS - Learning Management System
- 1. LOLA - Learning Object and Learning Activities
- li. LOM - Learning Object Metadata
- lii. LOR - Learning Object Repository
- liii. LQ - Learner's Quanta
- liv. LTSA - Learning Technology System Architecture
- lv. MAE - Mean Absolute Error
- lvi. MERLOT - Multimedia Educational Resource for Learning and Online Teaching
- lvii. MF - Membership Function
- lviii. MIQ - Machine Intelligence Quotient
- lix. MOM - Mean of maxima
- lx. Moodle - Modular Object-Oriented Dynamic Learning Environment
- lxi. MSE - Mean Square Error
- lxii. OCW - OpenCourseWare.
- lxiii. OER - Open Educational Resources
- lxiv. OUSD P&R - Office of US Secretary of Defense for Personnel and Readiness
- lxv. PHP - Hypertext Pre-Processing
- lxvi. PROMETEUS - Promoting Multimedia Education and Training in European Society,
- lxvii. RMSE - Root Mean-Squared Error
- lxviii. RSQ - Root Sum Square
- lxix. SAM - Student Activities Meters

- lxx. SCORM - Sharable Content Object Reference Model
- lxxi. SCOs - Shareable Content Objects
- lxxii. SDLC - System Development Life- Cycle
- lxxiii. SIF - Schools Interoperability Frameworks
- lxxiv. SOA - Service Oriented Architecture
- lxxv. SPSS - Statistical Package for Social Sciences
- lxxvi. SVM - Support Vector Machine
- lxxvii. TOM - Theory of Mind
- lxxviii. UoL - Unit of Learning
- lxxix. URL - Uniform Resource Language
- lxxx. WAT - Weblog Analysis Tool
- lxxxi. WIES - Web-based Intelligent Educational System

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CHAPTER ONE

INTRODUCTION

1.1 General Overview

E-learning, the term that has become the *de facto* name for electronic learning, refers to application of Information Technology (IT) to teaching and learning (Winterstein, 2007). The technology has attained a worldwide acceptability as a tool in distance, open and blended learning (Dai and Zhang, 2008). It has indeed become an important part of learning system playing either complementary or supplementary roles (Chayanukro, Mahmuddin and Husni, 2012). Over the years, several E-learning standards have been promulgated to facilitate qualitative and interoperable E-learning contents and E-learning components (Stracke, 2010). Advents of standards for E-learning as available for other technologies like electricity, railway and car according to Siegele (2003) is an indication of its popularity, acceptability and maturity.

However, the absence of face to face teacher – learner interactions in E-learning systems is a major weakness of the platform (May and George, 2011). Other limitations of the platform in Afolabi and Adagunodo (2012) include weak performance evaluation of the students and improper deployment of needed courseware. These deficiencies necessitate a well articulated learning design and activities monitoring model that could bridge the gap between the two highly researched extremes of the E-learning systems. At the initial end are the E-learning techniques for adaptive content deliveries while at the other end is the learners' performance prediction and monitoring models. However since formal

experience is required for formal knowledge Sun and Finnie (2005), it would be highly instructive to have a quality control model in between the two extremes. The model should be able to monitor and evaluate learners' experiences as a measure of readiness for a summative evaluation.

Traditionally, learners' learning activities and commitments to study are monitored using techniques such as class attendance, participation in class discussions, assignment submissions and performance in quiz. In E-learning, great efforts have also been made to replicate these operations. Prominent of these approaches is the adoption of visualization and statistical techniques to render the log-file's data from Computer Mediated Communication (CMC) platforms. Critical issue with this approach among others is its reliance on the teacher for graph and statistical figure's interpretation and decision making.

Furthermore, most Learning Management System (LMS) such as BlackBoard, WebCT and Modular Object-Oriented Dynamic Learning Environment (Moodle) actualize interactivity by incorporating CMC platforms such as Forum, Chat, Wikis and others for lesson packaging. These socio-constructivist pedagogy approaches are adopted to surmount the effects of the unidirectional flow of information (learning resources) specified in the Institute of Electrical and Electronic Engineering – Learning Technology System Architecture (IEEE-LTSA) standard 1484.1-2003. IEEE-LTSA is a generic E-learning system conceptualization model that is pedagogical free. The pedagogical independence of the model informed the common features of most LMS, in which E-learning course developers are provided only with platform for content authoring and for technical tricks to make the lesson interesting and appealing to learners without considering how learner learns (Nor Azan and Wong, 2007).

Actualizing E-learning system with capabilities for learning design model and automatic learners' activities monitoring would require reworking the IEEE-

LTSA. The three IEEE-LTSA's components that would be majorly affected are the Learning resources store, the Evaluation process and the Multimedia information flow. The Learning design models would be integrated into the Learning resources store as a process, such that designed lessons could follow proven procedures. Similarly, the Multimedia information flow that is by default a unidirectional flow would be modified to bidirectional to facilitate interactivity. Also, the Evaluation process would be expanded to include a diagnostic evaluation process. Within the Diagnostic evaluation process, a neuro-fuzzy artificial intelligence model would be integrated to represent the teachers' knowledge for automatic competence assessment and intelligent support. In practice, learner's model are built on probabilistic techniques as in VanLehn (1998), biometric techniques Asteriadis, Tzouveli, Karpouzia and Kollias (2008), or soft computing techniques among others.

Consequently, it would be highly instructive to investigate and establish the implications of learning design models on learners' activities explorations and academic performance. Also, it would be essential to investigate the machine learning approaches that would be the best for learners' activities monitoring, hence, the crux of this research.

1.2 Statement of the Problem

Contemporary E-learning systems are limited by the issues of courseware packages that do not guarantee learning, and that of inefficient mechanisms for learner activities evaluation. The former is due to the passive space provided for lesson design without instructional design support. The later is because the available visualization techniques - statistics and graph are internal to the LMS Arnold (2010), Blanco, Serrano, Freire, Mantnez and Fernande (2013), thereby require teacher's attention for statistic and graph interpretations and evaluations.

The efficiency of the teacher in this regard is dependent on access to Internet, size of the class and his time schedules.

Hence, for lack of quality control mechanism, an online-lesson may be poorly packaged such that learning may not take place in the student. In conventional classes teacher could psychologically determine the state of the class and promptly make necessary pedagogical adjustments. However, having such situation in a virtual class where face-to-face teacher/learners' interactions is missing would be highly detrimental and should be avoided. On the other hand, the visualization techniques and the complexity log files upon which they are built have been described as having low usability (Baker and de Carvalho, 2008), they are limited by timeliness and accuracy (May, George and Prevot, 2007). Furthermore, in the words of Ceddia, Sheard and Tibbey (2007) the abstractions and presentations based on these approaches are only appropriate for behavioural comparison. They can only measure awareness and self reflection (Govaerts, Duval, Verbert and Pardo, 2012). Other limitations identified by May and George (2011) are pedagogical and technical support issues.

To this end, this research formulates activities driven E-learning system that integrates instructional design theories for guided design and an artificial intelligence model for automatic competence assessment. The work alleviates the limitations of the pedagogy free platforms and ameliorates the challenges of learners' activity monitoring by visualization or statistical approaches.

1.3 Aim and Objectives

The aim of this research is to develop and implement a neuro-fuzzy learners' activities evaluation model.

The specific objectives are to:

- i. formulate learning activity driven E-learning system architecture;

- ii. develop a neuro-fuzzy learners' activities evaluation model;
- iii. implement the architecture and the developed neuro-fuzzy model in Open Source LMS;
- iv. validate the developed learner model and verify the efficacy of pedagogy on learners' academic performance

1.4 Motivation for the Research

The popularity and acceptability of E-learning platform for online distance and blended learning fortify the need for interactive system with adequate quality control mechanism. The research is therefore informed by the popularity and adoption of E-learning system, with the consequentially large students' enrolments. In such circumstances, learning activities tracking, monitoring and support methods that heavily rely on the teacher may be inefficient due to other engagements in research and community development. It is also informed by the facts that a lot of attention has been given to adaptive content delivery to take care of students with diverse learning style, entry knowledge and other preferences. However, the same cannot be said of monitoring learners' extents of lesson coverage quantitatively and qualitatively.

Furthermore, the inspiration for the research is reinforced by the availability of proven learning design theories and soft computing paradigms with the required Artificial Intelligence (AI) armamentarium for building system with very high Machine Intelligence Quotient (MIQ). The fact that AI models can be integrated into LMS, especially open source LMS like Moodle for automatic operations is another important impetus.

1.5 Scope of the Study

Student modelling is a purposeful exercise and the goals normally determine its metrics, functions and methodologies. This study is not specifically for learners' cognitive evaluation; it focuses mainly on tracking and evaluating learning activities as a measure of quantitative and qualitative coverage of lessons in E-learning systems. It is premised on the facts that students with high performance index usually achieve better grades and vice versa. Furthermore, the study concerned itself only with quantitative data indicator, not the contextual quality of the traces. The Learning Design (LD) theories being considered for Moodle lesson packaging are limited to Merrills, Dick and Carey, ADDIES, Gagnes and Kemp's models. The developed AI model and the LD modeled lesson were only integrated into Moodle as external service (add-on). Activities of the enrolled students in the integrated platform for CSC 306 were monitored for a semester. Furthermore, from the several available techniques of the soft computing paradigms, the synergy of the Neural Networks (Black box) and Fuzzy logic (White box) was explored to formulate the Neuro-Fuzzy (Gray box) model.

1.6 Significance of the Study

The study will provide a platform for packaging pedagogically grounded courseware and proffer the mechanism for measuring student's explorations of the courseware. It will provide quality assurance platform for curriculum monitoring and for evaluating level of learners' participation that will be devoid of human, bureaucratic and other logistic constraints that characterized the conventional methods. It would therefore serve as a tool for objective short-listing of learners for final examination based on quality of experience and participation. Thus, it would reduce the failure rates and improve the quality of

education. The study is also a demonstration of IEEE-LTSA extensibility and Neuro-fuzzy model capacity for modelling student exploratory behaviours.

1.7 Thesis Organization

The review of related literature is presented in Chapter Two. In Chapter Three, the research methodologies used for the accomplishment of the objectives are discussed. The discussion of the research results are presented in Chapter Four. In Chapter Five, the conclusion and recommendations made are presented.

CHAPTER TWO

LITERATURE REVIEW

2.1 E-learning and its Standards – An overview

The overall intent of this research is to enhance E-learning systems operations and usefulness. It is therefore considered essential to review the concept of E-learning for clarity. Similarly, the efforts that have been made by various bodies in promulgating relevant standards to facilitate E-learning system implementation, quality and interoperability need to be understood.

2.1.1 Concept of E-learning

E-learning has emerged as the *de facto* term (Winterstein, 2007) for what can also be called Web-based learning or on-line education. It refers to mode of education that involves the creation, storage and dissemination of teaching / learning resources using Information Technology (IT). It can be thought of as the combination of learning services and technology to provide high value integrated learning: anytime, anyplace (Babu, 2001). Some of its key benefits are that it provides an increased quality and value of learning through greater students' access. It extends education to the disadvantaged sectors of the society at a reduced cost. E-learning is continuously gaining popularities and acceptability among academic, business and professional communities. Attesting to the popularity and prospect of E-learning, John Chambers - the CEO Cisco System in 1999 stated that "the next big killer application for the Internet is going to be education; education over the Internet is going to be so big it is going to make e-mail look like a rounding error" (Winterstein, 2007). E-learning has numerous

players, playing various roles, using different tools on different platforms. Therefore there is need for standardization to ensure harmony in the industry.

2.1.2 E-learning Standardization and Purpose

Standard can generally be defined as "documented agreements containing technical specifications or other precise criteria to be used consistently as rules, guidelines or definitions of characteristics, to ensure that materials, products, processes and services are fit for their purposes" (ISO, 2004). Standard is said to be a *de jure* standard if it emerges by official directives or by law, but it is known as a *de facto* standard when it is a product of popular convention or general acceptability (Winterstein, 2007). The significance of standard appears in all spheres of human existence. Standards generally facilitate, ensure and enhance products usability, durability, interoperability and accessibility. According to Friesen (2004), the development of technical standards in E-learning can be seen as an indicator of its maturation. In the words of Siege (2003), "Railways, electricity, cars and telecommunication all learned to love standards as they came of age. At a certain point in their history, it became clear that rather than just fighting to get the largest piece of the pie, the companies within a sector needed to work together to make the pie bigger. Today, the IT industry is finally getting the standards religion". The overall essence of standard can be seen in the effects/efforts ratio, in the economic benefits, interoperability and quality development. The scopes of the interoperability according to Stracke (2010) are internal, directional, mutual and general. The quality dimension of a standard can be in its potential, in its process and in its result. The types and purpose of E-learning standard which can also be referred to as the domains and entities of E-learning standards are the conceptual standard, the level standard, and the implementation standard.

The implementation standards are developed to ensure the interoperability within all domains of E-learning, they require 100% compliance. The level standards define the quality level expected of E-learning applications; it is often used as bases for certification. The level standards are out of the scope for formal standard because they could be a product of policy developers, or decision makers within and outside the host organization. The conceptual standards are developed to ensure generic and theoretical solutions to compare and harmonize the entities and objects in E-learning systems. The conceptual standard can support the level and the implementation standards. It supports the former via provision of generic framework and the later by its adoption as shown in Figure 2.1.

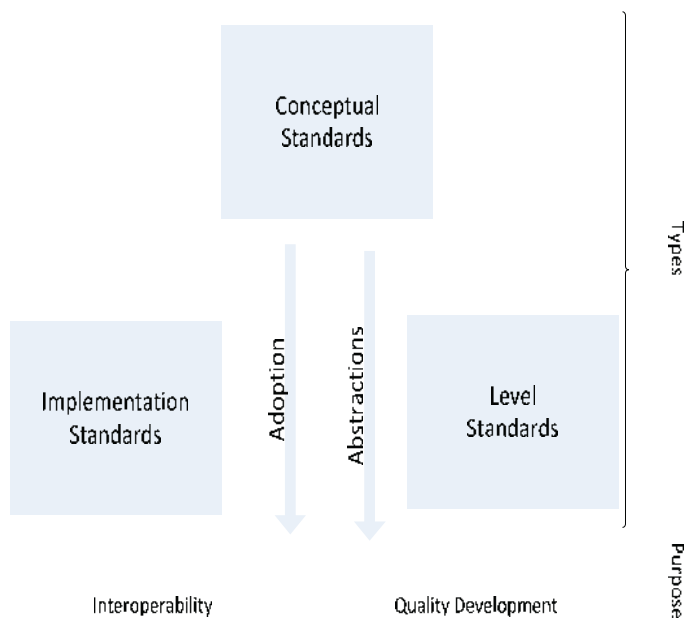


Figure 2.1: Types and Purpose of E-learning Standards (Stracke, 2010)

2.1.3 E-learning Standard Bodies

The quest to ameliorate the effects of high costs (time, efforts and resources) of developing educational contents that are not portable to other platforms prompted some organizations to proffering patterns and guidelines for E-learning contents and components Blanco et.al (2013). A handful of such organizations and bodies that have contributed to the development of E-learning standards are generally refers to as E-learning Standard Bodies. What becomes E-learning standard are initially promulgated has E-learning initiatives. The body that accredits E-learning initiatives and graduates them to E-learning standard is the International Standards Organization (ISO), accessible at <http://www.bsi-global.com>. Other prominent E-learning bodies are; the Instructional Management Systems (IMS Global Learning Consortium), accessible at <http://www.imsglobal.org> ; Institute of Electrical and Electronics Engineers Learning Technology Standards Committee (IEEE LTSC), accessible at <http://jtc1sc36.org> ; Aviation Industry CBT Committee (AICC) accessible at and Advanced Distributed Learning Initiative (ADL) accessible at <http://www.adlnet.org> . Other relevant bodies are ADLNet/SCORM - Advanced Distributed Learning Network/Sharable Content Object Reference Model, accessible at ADLNet/SCORM - <http://www.adlnet.org>; CEN/ISSS-the Centre de European Normalisation/Information Society Standardisation System, CEN/ISSS-accessible at <http://www.cenorm.be/iss>; DCMI - Dublin Core Metadata Initiative - accessible at DCMI - <http://www.dublincore.org>; PROMETEUS - Promoting Multimedia Education and Training in European Society, accessible at PROMETEUS -<http://www.prometeus.org>; ARIADNE - Association of Remote Instructional Authoring and Distribution Networks for Europe, accessible at ARIADNE - <http://www.ariadne-eu.org> and AICC - Aviation Industry CBT (Computer-Based Training) Committee accessible at AICC -<http://www.aicc.org>.

These bodies over the years formulated and published several initiatives and standards covering the three types identified. Some implementation standards are Content Metadata, Content Packaging, Learner Profile, Learner Registration and Content Communication. The conceptual standards include IEEE- Learning Technology System Architecture (LTSA), Sharable Content Object Reference Model (SCORM) and Schools Interoperability Frameworks (SIF). Overview of some standards formulated by these bodies either as implementation standards, conceptual standards or level standards are summarized in Table 2.1.

2.2 Zooming in IEEE-LTSA and SCORM

The peculiar relevance of IEEE’s Learning Technology System Architecture (IEEE LTSA) and Advanced Distributed Learning's SCORM E-learning standards to this study informed the need for detail review. The IEEE-LTSA being a generic reference model provides require bases for anchoring this initiative, while the ADL-SCORM is for packaging pedagogical interoperable E-learning content.

2.2.1 IEEE Learning Technology System Architecture (IEEE LTSA)

The IEEE Learning Technology System Architecture (IEEE-LTSA) is from the family of IEEE Standards for Learning Technology Systems (Bianco *et.al.*, 2013). The reference number for the IEEE- LTSC is ‘IEEE Std 1484.1-2003’. It is one of the releases of standards sponsored by the Learning Technology Standard Committee of IEEE Computer Society. The contents of the standard provide informative and normative technical descriptions of a Learning Technology System Architecture (LTSA).

Table 2.1: E- Learning Standards and Corresponding Standard Bodies

Standards	Purpose	Standard Bodies					
		IMS	ADL SCORM	Dublin Core	IEEE LTSA	ISO	AICC
Metadata	Labeling and indexing of content for easy storage, search and retrieval across repositories and platforms.	√		√	√	√	
Content Packaging	Specifications for inter-operability of courses among learning systems. It comprises of the learning contents, the instructions, the rules, the sequence and navigations.	√	√		√	√	√
Learner Profile	Designed to allow exchange of learner information across systems and platforms. It usually include personal data, learning plans, learning history, accessibility requirements, certifications and progress.	√			√	√	

Learner Registration	Determine what offerings should be made available to a learner via the Learner registration information.	√				√	√	
Content Communication	Standardized communication protocols and data models for sharing learner competency, course grade and completion	√	√				√	
System Conceptualization	Developed to ensure generic and theoretical solutions to compare and harmonize the entities and objects in E-learning systems.	√				√		

The informative wordings provide helpful information, clarifications of the text, examples and guidance. They do not contain any technical requirement and therefore they do not form an integral part of this standard. The normative wordings on the other hand are the essence of this standard. It specifies the technical requirement and conformity assessment that is based on normative wording. The IEEE LTSA standard

"specifies a high level architecture for information technology supported learning, education, and training systems that describes the high-level system design and the components of these systems. This Standard covers a wide range of systems, commonly known as learning technology, education and training technology, computer-based training, computer assisted instruction, intelligent tutoring, metadata, etc. This Standard is pedagogically neutral, content-neutral, culturally neutral, and platform-neutral. This Standard (1) provides a framework for understanding existing and future systems, (2) promotes interoperability and portability by identifying critical system interfaces, and (3) incorporates a technical horizon (applicability) of at least 5-10 years while remaining adaptable to new technologies and learning technology systems. This Standard is neither prescriptive nor exclusive." (IEEE, 2001).

According to IEEE LTSA, the overall intention of developing system architectures is to discover high-level frameworks for understanding certain kinds of systems, their subsystems, and their interactions with related systems. Architecture is not a blue print for designing a single system, but a framework for designing a range of systems over time, and for the analysis and comparison of these systems. By revealing the shared components of different systems at the right level of

generality, an architecture promotes the design and implementation of components and subsystems that are reusable, cost effective and adaptable. The architectural framework developed in this standard neither address the specific details of implementation technologies necessary to create the system components, nor the management systems (learning material lifecycle, quality assurance, access control, or user administration) necessary to manage a learning technology system. The standard only identifies the objectives of human activities and computer processes and their involved categories of knowledge.

2.2.2 IEEE LTSA Overview

The architecture specified five (5) refinement layers. Four of these layers are informative while the third layer (layer 3 - the system components) is normative. These refinement layers are usually called, from highest to lowest levels as follows:

- i. Learner and Environment Interactions (informative): this layer abstracts the interaction of learners among themselves and with the environment as conditions for knowledge acquisition, formulation and discovery. Though a unidirectional arrow was used to indicate the information flow from the environment to the learner, thereby portraying the learners as a dogmatic receiver of information. Furthermore, the concern component of the environment is not specified.
- ii. Learner-Related Design Features (informative): the concern of this layer is the effect learners have on the design of learning technology systems.
- iii. System Components (normative): this is the only normative layer in the architecture. It describes the process, the stores and the information flows that constitute the abstract component-based architecture.

- iv. Stakeholders Perspectives and Priorities (informative): Describes learning technology systems from a variety of perspectives of the stakeholders. It references the subsets of the system components layer.
- v. Operational Components and Interoperability — codings, APIs, protocols (informative): the layer describes the generic "plug-n-play" (interoperable) components and interfaces of information technology-based learning technology architecture, as identified in the stakeholder perspectives. The diagram of the IEEE-LTSA is as shown in Figure 2.2.

2.2.3 IEEE LTSA System Components Layer

The LTSA System component layer identifies four processes (learner entity, evaluation, coach, and delivery process), two stores (learner records and learning resources) and thirteen information flows among these components (behavioral observations, assessment information, learner information (three times), query, catalog info, locator (twice), learning content, multimedia, interaction context, and learning preferences).

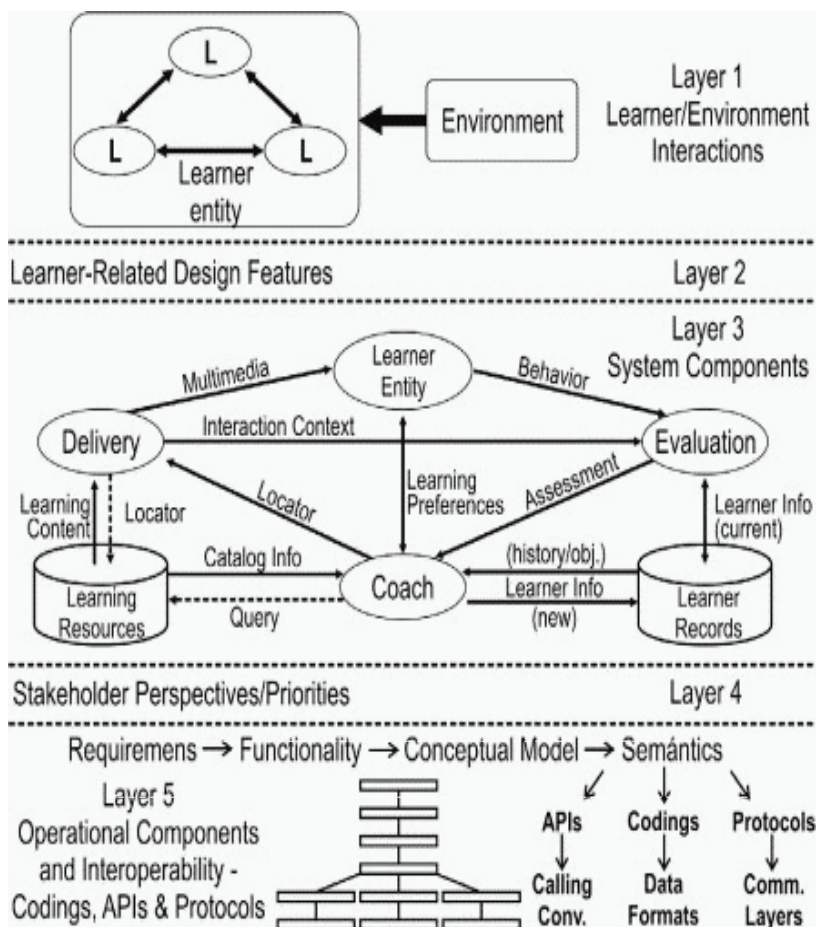


Figure 2.2. The LTSA abstraction-implementation layers.

(IEEE 1484 LTSA, 2001)

The IEEE LTSA draft document explain its overall operation in the following form: (i) the learning styles, strategies and methods are negotiated among the learner and other stakeholders and are communicated as learning preferences; (ii) the learner is observed and evaluated in the context of multimedia interactions; (iii) the evaluation produces assessments and/or learner information; (iv) the learner information is stored in the learner history database; (v) the coach reviews the learner's assessment and learner information, such as preferences, past performance history, and, possibly, future learning objectives; (vi) the coach searches the learning resources, via query and catalog info, for appropriate learning content; (vii) the coach extracts the locators from the available catalog info and passes the locators to the delivery process, and (viii) the delivery process extracts the learning content from the learning resources, based on locators, and transforms the learning content to an interactive multimedia presentation to the learner.

The IEEE LTSA model is modified in this study to reflect the pedagogical content packaging and activity monitoring.

2.2.4 Advanced Distributed Learning's SCORM

The Sharable Content Object Reference Model (SCORM) is a product of the ADL Initiative which was established in 1997 at the US Office of Secretary of Defense for Personnel and Readiness (OUSD P&R) to standardize and modernize training and education management and delivery. The vision of the ADL Initiative according to ADL (2011) was to;

"Provide standards and technology that would enable the Department of Defense (DoD) to have access to the highest-quality learning and performance support that could also be tailored to individual needs and delivered cost-effectively, at the right time and in the right place".

Therefore, to meet its mission, the ADL Initiative developed the Sharable Content Object Reference Model (SCORM) and the ADL Registry. SCORM integrates a set of related technical standards, specifications, and guidelines designed to meet SCORM's high-level requirements of accessibility, reusability, interoperability, and durability of content and systems. SCORM content can be delivered to learners via any SCORM-conformant Learning Management System (LMS) that uses the same version of SCORM. ADL employs a structured, adaptive, collaborative effort between the public and private sectors to develop the standards, tools and learning content for the learning environment of the future. The vision of the ADL Initiative is to provide access to the highest-quality learning and performance aiding that can be tailored to individual needs and delivered cost-effectively, anytime and anywhere. (Winterstein, 2007). The key benefits of SCORM include:

- i. The provision for students and educators to scale, share and reuse learning content
- ii. Making learning content discoverable through interoperability with content repositories
- iii. Enabling the development of adaptive learning systems that can assemble content to meet the learner's needs "on the fly"

2.2.5 Description of SCORM System

SCORM adopted the learning object approach to learning content. In that learning content is broken down into Sharable Contents Objects (SCOs). SCORM focuses on two critical pieces of learning content interoperability:

- i. It defines an aggregation model for packaging learning content
- ii. It defines an API for enabling communications between learning content and the system that launches it

SCORM also divides the world of learning technology into functional components.

The key components are

- i. Learning Management Systems (LMS)
- ii. Shareable Content Objects (SCOs)

Figure 2.3 is the functional components of SCORM system while Figure 2.4 is the SCORM generalized LMS.

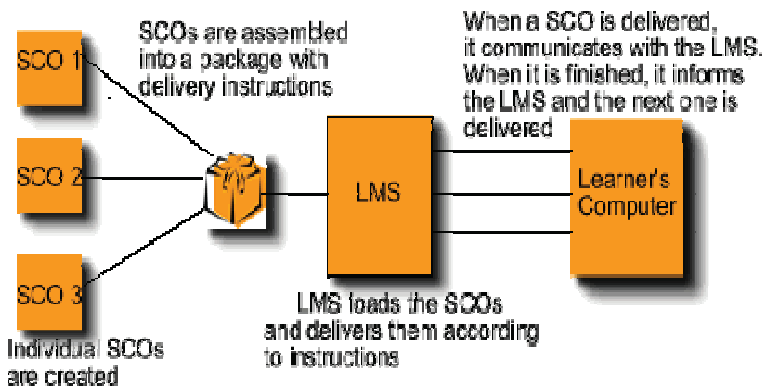


Figure 2.3: Functional Components of SCORM System. (Techlearn, 2001)

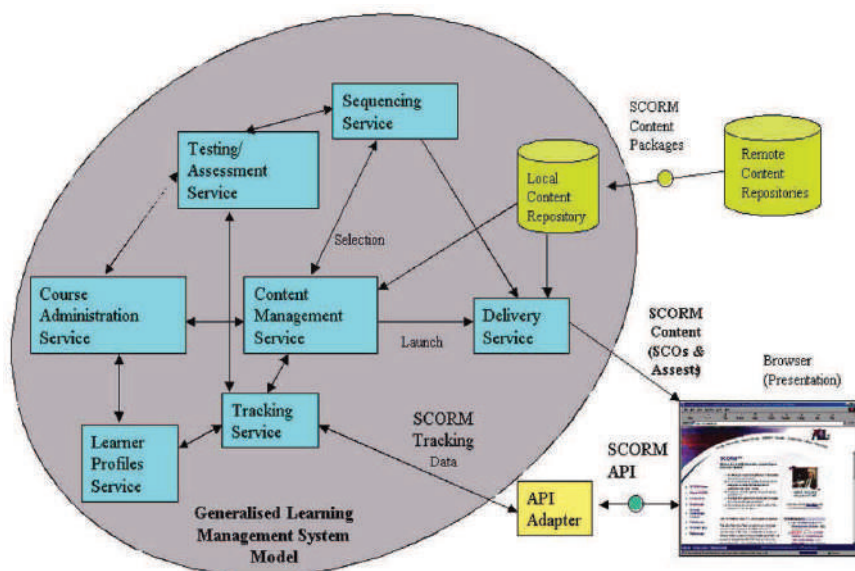


Figure 2.4: The SCORM generalized LMS. (ADL, 2011)

2.3 Forms of E-learning System

E-learning Systems can be categorized according to their scale, operational mode and applied technology. The following are explanations of some categories of E-learning.

2.3.1 Adaptive E-learning System

Adaptive E-learning System (AES) is an enhanced E-learning System that improves the usefulness and effectiveness of E-learning System by adapting the presentation of information and overall linkage structure to individual users in accordance with their knowledge and behaviour, (Esichaikul *et.al.*, 2011). An E-learning system is said to be adaptive when it delivers course content to the learners in a flexible and conditioned pattern based on individual learner's specific characteristics and peculiarities. This type of E-learning System capitalizes on the learner's characteristics in order to optimize the learning outcomes (Brusilovsky and Peylo, 2003). The overall goal of Adaptive E-learning System is to improve student's quality of knowledge acquisition by keeping tracks of usage and accommodate content automatically for each learner. The main component of an adaptive E-learning system is the student model. The other two are the domain model and the adaptive model.

The student model contains domain specific and domain independent information of the student. The domain specific information captures the knowledge level of the student on the subject matter, it is therefore, known as student knowledge model. The domain independent information documents the general skills, preferences and behaviours of the student.

The domain model comprises of two main parts; the course content and the delivery system. The domain model acts as a repository that consists of topics, contents, pages or nodes, and navigation links related to the design structure of

the represented data in a given domain. The delivery system supports all contents types and formats.

An adaptive model purposefully relates the domain model with the student's model. The process commences with selection of representative nodes and followed by nodes presentation in an appropriate version as required by the knowledge types. Nodes can be classified into three types of knowledge; basic knowledge, procedural knowledge and conceptual knowledge (Shute and Towle, 2003). Generally, the four processes of adapting teaching and learning are adaptive content aggregation, adaptive presentation, adaptive navigation and adaptive navigation support (Esichaikul *et.al.*, 2011).

2.3.2 Intelligent Educational System

Intelligent Educational System (IES) are computer programs that adopt Artificial Intelligence (AI) techniques to mimic human teacher. A teacher is required to possess the knowledge of the subject matter, the knowledge of the students and the knowledge of the teaching methodology. To simulate these three types of knowledge, a typical IES consists of four modules; the expert module, the student model module, a tutoring module and a user interface module (Brusilovsky, 1994) and (Sabbir, 2004).

The expert module comprises the facts and rules of a specified body of knowledge intended for the student. The student model module represents the current profile of the student in the educational system. They are the belief of the system about the student and therefore serve as the pivot for other components. The tutoring module decides and provides appropriate pedagogical activities for a student by considering the current profile of the student and the nature of the subject matter. The user interface module is the platform for the system and

students interaction. The intelligent and adaptability of the system depends largely on the student model.

In the work of Wenger (1987), IES was discussed as Intelligent Tutoring Systems (ITS). The four components identified for the purpose of design and conceptualizations are: The domain knowledge, the pedagogical module, the student model and the interface.

The domain knowledge aimed to store, manipulate and reason with knowledge of the domain being taught. The pedagogical module provides information about the teaching strategies that should be used for various categories of students. The student model stores and analyzes information of student's current state of knowledge and personal characteristics. The Interface, handles the form of communication between the ITS and the students. According to Stathacopoulou *et al.* (1999), the student model seems to be the most important component of ITS so that it could provide the capability to adapt its behaviour to the specific traits of the students.

The usage of the student model in any intelligent educational system is to adapt all other components of IES so as to satisfy the needs of individual learners. In the tutoring module for instance, each of its functions can be adapted using the student module. Some of its functions include among others the knowledge development, error remediation, domain content representation, exploration space control, knowledge diagnostics, strategic functions, prediction functions and assessment functions (Kashihara, Kinshuk, Oppermann, Rashew, and Simm, 2000) as in (Binglan, 2001).

2.3.3 Web-Based Intelligent Educational System

When global accessibility is required, the ordinary stand alone intelligent educational system can be ported to Web to produce a Web-based Intelligent

Educational System (WIES). The WIES is continuously growing in acceptance world-wide because of its innumerable advantages. Some of these include the geographical or physical classroom independency, cross-platform deliverable, individualized learner adaptation, centralized maintenance and cost effectiveness. The implementation of the WIES is by redistributing the basic components of the IES among the server and the client, in addition to some necessary internet services component to facilitate client-server communication. The three types of WIES architecture identified in Binglan (2001) are; the replicated architecture, the centralized architecture and the distributed architecture.

In the replicated architecture, the server serves as the repository of the intelligent tutoring system. The student is expected to download the package from a specified URL into a personal computer or related devices for execution. Appropriate plug-ins relevant to the internet technology employed may be downloaded and installed to get system running. The advantage of this architecture among others is that the students can work offline and may go online for updates. The architecture is limited to the fact that several versions of the system may be running on students systems.

When all the functions of intelligent tutoring system are performed in the server, such system architecture is known as centralized architecture. The students need to be online all the time to be connected to the system. The student interacts through the HTML form via the common gateway interface to the server. Central coordination and administration is an advantage in this architecture but it is limited by possible challenges of client/server communication due to connectivity and stateless features of CGI programs.

The third architecture is distributed architecture, in which the functions are shared between the front end platform and the server - backend platform. The functions related to users interactions are implemented as Java applets and Java

scripts embedded in HTML pages as the front end. The server plays the usual role of repository of administrative and sharable contents. This architecture shares the strengths as well as the weaknesses of the two other architectures.

2.4 The Interplay of Learning Activities and Learning Design Models

This research is premise on the fact that knowledge is a transformation of experiences, and that experiences are products of learner's interactions with the learning contents. For the interactions to result into expected experiences it must be properly planed and its implementation monitored. The technique that is demonstrated in this work postulates that the measured learners experience is a good indicator of the acquired knowledge, and that knowledge acquisition is guaranteed when the learning activities is based on learning design models.

2.4.1 Knowledge, Experience and Learning

Over the millennia, there have been several attempts at defining the concept of knowledge and experience by Psychologist, Educationist and Scientist. Till date, there is no consensus on the definitions of the two concepts, what is however clear is that they are both intelligent assets of man. Several attempts have been made by computer scientists to replicate or represent knowledge and experience in machine as Artificial Intelligence (AI).

Knowledge is a construct or an atom used in understanding the cognitive (or intelligent system) possess that is used to take effective action to specific goal Voss (1996). In computer science, knowledge is defined as an object concepts and relationship that are assumed to exist in some areas of interest (Sun and Finnie, 2004). Knowledge exists everywhere and knowledge may be elicited in everything. For instance, immensurable knowledge exists in encyclopedias,

handbooks, manuals, lecture materials, brain of man and on the internet (Sun and Finnie, 2005).

Learning is the process whereby knowledge is created through the transformation of experience (Kolb, 1984). Central to the process of transformation is reflection. According to John Dewey (1859-1952) an American educator and philosopher as in Dewey (1938). "Experience happens, it is unavoidable. The problem for teacher and student is to make learning out of our experience". Dewey believed that "knowledge is not so much a 'given' as it is a 'creation' and that it is individually and communally constructed by people as they engage in and reflect on the world around them". It is therefore deducible from the above that the vehicle for acquisition of knowledge (Learning) is experience. Without adequate experience there cannot be a genuine knowledge. Catalyst for learning is not just the teacher, the book, the situation or the environment but the role of the learner in the learning experiences. This is because, the most powerful learning occurs when the learner is active in the process (Anderson and Eithier, 2004).

In Kolb (1984), reflection was identified as a necessary tool of transforming experience to knowledge. He further outlined reflection cycle as: Concrete Experience - Reflective Observation - Abstract Conceptualization - Active Experimentation. Reflection typically includes reconstructing the experience, making connections to prior knowledge or skills, testing understanding and making decisions about how to apply the knowledge or skill in a new situation. Some methods for promoting reflection include oral conversations, written responses through diaries, journals, portfolios and exhibitions. Reflection requires concentration, attentiveness and meditation. If the extent of experience and level of concentration of a learner can be measured, then it will be possible to presume the amount of learning that has taken place in a learner. This assumption can formally be verified using summative evaluation. It should be possible to

track these parameters from the user interface in an E-learning platform if they were pre-coded into the courseware as learning activities. When this type of tools is available in adaptive E-learning system it will be pretty possible to determine the learning rate of a learner and use it as bases for administrative decisions.

2.4.2 Learning Activities

Learning can be viewed as a process of acquiring knowledge, skills and behaviour. It is a process that is usually facilitated by teaching, experiencing (doing or observing) and dialoguing (with self or with others). Dialogue or interaction is indeed an important learning activity, in the words of Karampiperis and Sampson (2005), learning activities is a triple containing the contents, the actors and the corresponding interactions. Furthermore, Shale and Garrison (1990) stress that without interactions, instruction may simply become "passing on content as if it were dogmatic truth, and the cycle of knowledge acquisition, critical evaluation, that is important for the development of higher-order thinking skills is nonexistent". So, without interaction, it may be impossible to facilitate learning.

In the traditional classroom settings teacher and students interactions occur spontaneously, promptly and in real time. The face-to-face platform provides the teacher an opportunity to study the class mode and read students body language to determine the sequence and pace of the lesson. The teacher demonstrates his/her experience, wisdom and charismas sufficiently to facilitate understanding of the lesson and also to correct any lesson design errors.

Nonetheless, this important teacher-learner interaction is highly confined if not totally absent in E-learning. The most prominent of all forms of interactions in E-learning is learner-content interaction. Hence, accomplishment of appreciable quality of learning on E-learning platform would be a function of quality of interaction built into the courseware at the design stage. In the words of Hirumi

(2002) to facilitate learning the key interactions that occur spontaneously in traditional teacher-directed classroom environment must be carefully planned and managed as an integral part of E-learning. The challenge is how to package learning content with all the required learning activities to facilitate learning.

2.4.3 E-learning Interactions

Quality of interactions is a strong determining factor for the success or otherwise of a lesson. Interaction in this context could refer to the process of a learner accessing and reading content of web pages Carlsson and Repman (2009), or it may involve learner and learning system responding to one another synchronously. Essentially, Borsook (1991) identified seven characteristics of interpersonal communication that needs to be simulated in interactive program as immediacy of response, non-sequential access of information, adaptability, feedback, options, bi-directional and interoperability. Hirumi (2002) stressed that interactivity among participants is an important element in any form of distance learning because it reduces feeling of isolation, anonymity, dissatisfaction, poor performance and dropout among participants.

Looking at it from the perspective of active learning pedagogy, learning takes place as result 'Experience of' and 'Dialogue with'. The 'dialogue with' here refers to the interactivity with self and with others, while 'experience of' could be through observation or by doing. This conforms to the 'Communication based' taxonomy of interactive classification posited by Moore (1989) as student-student, student-teacher and student-content interactions. Other communication based taxonomies are learner interface interactions, learner-instructional, learner-designer and learner-stakeholders interactions, (Hirumi, 2002).

Other major taxonomies for classifying interactions are Purpose-based, Activity-based and Tools-based taxonomies. The Purpose-based taxonomies were coded by

Moore (1989) as confirm, pace, inquire, navigate and elaborate. The purpose-based interaction according to Northrup (2001) are interaction with content, collaborate, converse, monitor/ regulate learning and to support performance. The levels of Activity-based taxonomies according to DOD (2001) are level 1- Passive, level 2- Limited participation, level 3- Complex participation and Level 4- Real time participation. The Tool-based taxonomies according to Bonk and King (1998) are Electronic mail and delayed-messaging tools, remote access and delayed collaboration tools, real-time brainstorming and conversation tools, real-time text collaboration tools, and real-time multi-media and/or hyper media collaboration tools. Diverting from simple classification, Hirumi (2002) proposed a three (3) level framework to include: Learner- self interactions, learner- human and non-human interactions and, learner-instruction interactions.

2.4.4 E-learning Interactions Frameworks

There is plethora of frameworks in the literature as there are various classifications of interactions. Though these descriptive frameworks give brilliant insights into the nature and range of potential E-learning interaction, but, they neither illustrate relationship among them, nor prescribe practical guidelines for planning and managing cohesive set of interactions that comprise an instructional lesson, module or unit. To be effective, learning design interaction should be based on grounded instructional strategies, not the traditional teacher-directed methods that is based on educators past practices (Hirumi, 2002). Grounded design according to Hannifin, Hannifin, Land and Oliver (1997) is "the systematic implementation of processes and procedures that are rooted in established theory and research in human learning ". The three categories of grounded instructional strategies are Learner-Centred Approaches, Experiential Approaches and the Teacher-Centred Approach.

2.4.5 Learning Design Models

The terms Instructional Design (ID) and Learning Design (LD) are interchangeable used to describe instructional experiences which make the acquisition of knowledge and skill more efficient, effective and appealing (Merrill, Drake, Lacy and Pratt, 1996). It is a systematic process that is employed to develop education and training programs in a consistent and reliable fashion (Raiser and Dempsey, 2007). The processes are based on well researched and well tested pedagogical theories of teaching. They assumed that if appropriate process is used to package instructions, learning will take place, the outcome may either be observable or assumed. Reiser and Dempsey (2012) traced the concept of "Instructional design" to the B.F. Skinner's 1954 article titled "The Science of Learning and the Art of Teaching", that, in the article he stated that effective instructional materials, called programmed instructional materials, should include small steps, frequent questions, immediate feedback and allow self-pacing. However, according to Conole and Fill (2005), the concept of learning design sufficed prominently in educational technology literature in late nineties and early 2000s with the idea that "designers and instructors need to choose for themselves the best mixture of behaviourist and constructivist learning experiences for their online courses".

Instructional Design (ID) or Learning Design (LD) models can be distinguished from Instructional System Design (ISD) model. Usually, ISD is broad; they divide instructions into phases. The IDs are more focused they are subsumed into ISDs. The strategies of ID are Organizational, Delivery and Management. They are said to be prescriptive because they provide guidelines or framework for the organization, structuring and creating of Instructional activities. Common examples of instructional design models are Merrill's First Principle of Instruction, ADDIE Model, Dick and Carey Model, Kemp's Instructional Design Model and

Gagne's Nine Events of Instruction. Others are John Keller's ARCs model, Jeroen Van Merriemboer's 4C/ID model and Lev Landa's Algo-Hueristic Theory. The following are brief explanation of some of these models considered in this study.

2.4.5.1 Merrill's First Principles of Instruction

David Merrills in 1983 formulated a four phased first principle of instruction. His model suggests that the most effective learning environments are those that are problem - based and that involve the student in four distinct phases of learning. The phases are Activation, Demonstration, Application and Integration. Invariably, at the top level, the model posits that:

- i. learning is facilitated when learners are engaged in solving real-world problems;
- ii. learning is facilitated when existing knowledge is activated as a foundation for new knowledge;
- iii. learning is facilitated when new knowledge is demonstrated to the learner;
- iv. learning is facilitated when new knowledge is applied by the learner;
- v. learning is facilitated when new knowledge is integrated into the learner's world.

2.4.5.2 Gagne's Nine Events of Instruction

The Nine Events of Instruction was promulgated by Robert Gagne who is a behaviourist. He focuses on outcome (or behaviour) resulting from training. He also has to his credit the Taxonomy of Learning Outcome and Conditions of Learning. Gagne synthesizes ideas from both Behaviourism and Cognitivism to provide a clear template which is easy to follow for designing instructional events. In the words of Perry (2001), any instructional designers who follow Gagne's theory will likely have tightly focused and efficient instruction.

Gagne stressed that learning occurs in a series of learning events and to ensure that learning takes place each learning event must be accomplished before the next. The nine events are Gaining attention; Informing learners of objectives; Stimulating recall of prior learning; Presenting the stimulus; Providing learning guidance; Eliciting performance; Providing feedback; Assessing Performance; Enhancing retention and transfer (Gagne, 1988).

2.4.5.3 ADDIE Model

The ADDIE Instructional design model in its original form has five cyclical phases - Analyze, Design, Development, Implement, and Evaluate. Historically, the model originated from Florida State University as model to explain "the process involved in the formulation of an Instructional Systems Development (ISD) program for the military interservice training..." (Branson, Rayner, Cox, Furman, King and Hannum, 1975). All other ISD models are spin-offs or variations of ADDIE instructional model.

2.4.5.4 Dick and Carey Model

The Dick and Carey Systems Approach Model was published in 1978 by Walter Dick and Lou Carey in their book entitled 'The Systematic Design of Instruction'. The model addresses instruction as an entire system, focusing on the interrelationship between context, content, learning and instruction. In the model, components are executed iteratively and in parallel rather than linearly. The components of the System Approach Model according to Dick and Carey (1996) are Identify Instructional Goal(s); Conduct Instructional Analysis; Analyze Learners and Contexts; Write Performance Objectives; Develop Assessment Instruments; Develop Instructional Strategy; Develop and Select Instructional

Materials; Design and Conduct Formative Evaluation of Instruction; Revise Instruction; and Design and Conduct Summative Evaluation.

2.4.5.5 Kemp's Instructional Design Model

Jerold Kemp adopts a continuous implementation view to instruction design. The elements of Kemp model are usually arranged cyclically in an oval shape. The nine (9) elements are: Identify instructional problems and specify goals for designing an instructional program; Examine learner characteristics that should receive attention during planning; Identify subject content, and analyze task components related to stated goals and purpose; State instructional objectives for the learner; Sequence content within each instructional unit for logical training; Design instructional strategies so that each learner can master the objectives; Plan the instructional message and delivery; Develop evaluation instruments to access objectives; Select resources to support instruction and learning activities.

2.5 Learning Object Repositories and Open Educational Resources

The concept of openness is gaining acceptance in the educational sectors across the globe. Institutions make their courseware available online in a repository for sharing with little or no restrictions.

2.5.1 Open Educational Resources

Openness generally refers to unrestrictive accessibility, availability, transparency and participatory. Openness is one of the numerous tangible benefits of the advancement in internet and information technology. It has provided a platform for sharing of all sorts of resources across all sectors of human endeavour. In education sector for instance, Information and Communication Technology (ICT)

facilitates and enhances openness in educational resources for teaching / learning, research, and community development.

There are several ongoing projects and interventions aimed at promoting openness in education sectors worldwide. Open Educational Resources (OER) refers to collections of tutorials, lectures and presentations in various formats that are made available for public use. OER are rated based on the extent of openness; either secured or unsecured, extent of remixing, repurposing and possible redistribution. But, just as accessibility is an aspect of transparency, same it is for openness. The duo can however be enhanced by participatory and responsiveness.

Information technology controls the quality of OER. The earlier OER were built on Web 1.0 as in MIT OpenCourseWare (OCW). These first generations of OER were accessible but static. The advancement of Web 1.0 to Web 2.0 provides a more qualitative OER with platform for global participation and collaboration. This is as evident in Wikipedia for Encyclopedia, YouTube for Video collections, Facebook for Social Interaction. Open educational resources are also available at Connexions by Rice University accessible at <http://cnx.org>.

Though, OER being a developing technology currently have some challenges. Some of the challenges include standardization, usability, effects / impacts and copyrights issues among others. However, as the global community tackles these challenges it is essential that its advantages are maximally exploited. The academic community should not unnecessarily reinvent the wheel. It should be possible to harvest from the pool of resources, remix, repurpose and redistributed to satisfy a specific interest in terms of objectives and audience. Provision of a framework for harnessing, remixing and repurposing OER in repositories is one of the significance of this research.

2.5.2 Learning Object and Courseware

Learning objects are small reusable chunks of learning content that can be aggregated and sequenced into a coherent lesson. It is the E-learning equivalent of 'object' in object programming paradigm which can be independently reused and composed in order to construct a complete system. It is the elementary particles of an E-learning system (Wiley, 2002). Furthermore, Learning object has been defined as "any entity, digital or non-digital, which can be used, re-used or reference during technology supported learning", (IEEE, 2004). Varlamis and Apostolakis (2006) described conceptual content object model that establishes the relationship between content assets, learning object and lesson or courseware. The raw content assets are the individual fact, principle, concept, example, procedure and so on that can be assembled into a 'just right' Learning Objects. The assembling is usually guided by objectives. When learning objects are aggregated based on topics and themes then lessons or courseware emerged. The learning objects typologies identified by Churchill (2007) are presentation, practice and simulation objects, others are, conceptual, information and context representation objects.

Courseware is therefore the aggregated and sequenced learning content. It is usually prepared via Content Reusability Framework, which is the courseware construction environment that merely requests the course creator to search for relevant learning objects from the repository instead of creating all their learning contents (Brisilovisky and Peylo, 2003). The traditional courseware reuse model allows course creation to operate at a high level of abstraction. The approach saves development time and improves quality. The weakness of this approach is that it is based on a one-size-fit-all assumption.

To ameliorate this problem, several 'Information Architectures' have been developed. Some of them according to McMullen (2011) are: Adaptive

Educational Hypermedia (AEH), Adaptive Hypermedia Authoring Mode (AHAM), and Layered Adaptive hypermedia authoring model and its algebraic OperatorS (LAOS). They are all built with aim of selecting learning contents for learner and presenting them base on peculiar characteristics of the learners.

2.5.3 Learning Object Repository

The idea of Learning Object Repository (LOR) came about to provide a platform for E-learning community to share learning resources in a standard and interoperable format. In other words the LOR provides functionalities that allow educators worldwide to search, retrieve or add learning materials. Karampiperis and Sampson (2005) defined it as a kind of digital library that enables collection, management, sharing and reusing of dispersed learning resources. All learning objects and their metadata are stored in the LOR. The LOR are generally of two types; some store learning content and their metadata, while others store metadata only. Examples of LOR are the Multimedia Educational Resource for Learning and Online Teaching (MERLOT), Learning Object and Learning Activities (LOLA), the Gateway of Educational Materials (GEM) and digital library, MIT Open Courseware (OCW).

2.6 User Modelling and Requirements

For computer to understand the behaviour of the users and use such knowledge as bases for intelligent actions there is the need to make a machine representation of such. The technical term for the process of such accomplishment is known as users modelling. In this work, the focused users are the students and the teachers. The students' behaviours are models against the corresponding actions of the teachers. It is therefore considered essential to review the concept of modelling, its various types and some relevant user modeling initiatives in E-learning.

2.6.1 The Concept of Modelling and Purpose

Modelling is a purposeful process of producing a replica or a mock-up version of a natural or man-made entity. It is a process of formulating a representation of a whole or components of a reality in a given domain. Modelling has a lot of advantages in humanities, science and technology, that it could be used to study the various features of a system. It could also be used to predict the effects of variations and interactions of the features without exposure to possible risk. According to George and Bo (1995), the purpose of constructing a model of some aspect of reality is to understand some phenomenon of reality, making adequate predictions or retro-dictions, learning how to control the phenomenon in any desirable ways, and utilizing all these capabilities for various ends. Model of desirable man-made objects are however constructed, for the purpose of predicting operations, by which any conceived artificial object can be constructed so as to achieve the desirable objective within a given constraints.

All models are generally constructed with the intention of maximizing its usefulness. The accomplishment of this goal relies on the extent of managing the relationship between complexity, credibility and uncertainty which are the three key characteristics of a model. Accommodating uncertainty has become a necessary plague to accept and cope with, if the overall goal of Artificial Intelligence will be realized substantially. Though, there is no consensus on the relationship between the three characteristics of a model, what is however clearer is that, the more an uncertainty is accommodated in system the more the reliability of the system but less the complexity (George and Bo, 1995).

In the Artificial Intelligence community, uncertainty in a system has been handled using statistical approaches as well as the softcomputing approaches. The former was found to pose some challenges while the latter seems to be more robust and adequate for representing the uncertainty entrenched in most human

endeavours. The only key to success with all Bayesian network models lies in accurately representing the probability dependencies in the task domain (Conati, Gertner and Vanlehn, 2002). This is quite challenging, especially for the educational system which is the domain for this study. Teachers use common language expression like good, fair, poor and others to express learners' performance rather than probabilities. The combined strengths of Fuzzy Logic and Artificial Neural-Networks known as Neurofuzzy approach is the preferred modeling techniques for this study.

2.6.2 Student Modelling

Student modelling according to Self (1994) in Greer and McCalla (1994) is the process of creating and maintaining student model. Its components are Student model and Diagnostic module. These components are distinct but interwoven. The students model is simply a data structure of required students attributes, the diagnostic module performs diagnostic process that update the student model. Normally, the student model is expected to include all aspects of students' behaviour and knowledge that influences their performance and learning (Wenger, 1987). It is challenging to capture students' model data and it is even more challenging to interpret the information for a decision. A student model can be said to be the system's beliefs about the learner's knowledge, interests and other student's issues like goals, learning preferences and other dynamic features of the students. Student model in E-learning systems just like any other system users model intends to capture the relevant behaviour of the users, usually for the overall intention of adapting the system to the user's preferences and other peculiarities. A student model is one of the three core models of an adaptive E-learning system. The two other models are the domain model and an adaptive model. The two processes of student modelling or the two stages of students

modelling are the initialisation stage and the update stage (Esichaikul, Lamnoi and Bechter, 2011).

2.6.3 Initialization of Student Models

Initialization is the process of setting up the student model parameters. According to Self (1994), the three ways of initializing student model are explicit questioning, initial testing, or by stereotyping. Explicit questioning is used to elicit general information about students' background and personal preferences usually via questionnaire. The Initial testing method is a pre-test method where the learner is giving an explicit test that is analyzed for initialization of cognitive traits. The Stereotyping is said to be used when initialization attributes are acquired from group collections, hence, the system guess the initial data for a student from the pool.

2.6.4 Update of Student Models

After the initialization, it is essential to update the model continuously by building up the students' profiles in order to obtain the current data about the student. The sources of information used for updating student model could be the information currently stored in the student model, the current information stored in other components of the ITS and/or information gained through interaction between the students and the system (Binglan, 2001).

Methods of obtaining update information include; implicit acquisition, explicit acquisition, structures acquisition and historical acquisition. Implicit acquisition refers to the process of observing the actions of the student while engaging in the learning process. Explicit acquisition employs direct dialogues between the system and the students. Structured acquisition is by analyzing the interactions between curriculum elements for prerequisite and/or dependency. Historical

acquisition generally estimates the students' knowledge and capabilities from previous experience. (Kinshuk, Nikov and Patel, 2001).

These approaches are also referred to as Collaborative / Automatic techniques Brusilovsky (1996) or Intrusive / Non intrusive methods. Whenever the "asking the students" and/or initial questionnaire test are used, the model is said to employ Collaborative or Intrusive method. This is because the students are consciously involved in its data gathering. The method is very okay for some kind of students' model. In fact, it is the recommended technique for some domain independent modelling such as background and preferences. The collaborative or intrusive method was eulogized in the slogan for bypassing the student modelling problems proposed by Self (1990). The information gathered through the collaborative or intrusive method may however be customized, window-dressed and therefore subjective. On the other hand when the automatic or non-intrusive methods is used, it always reveals an undiluted behaviour of the students, this is because it does not activate the students consciousness.

2.6.5 Challenges of Student Modelling

Model initialization and model updating which are the processes involved in students modelling are quite challenging in their respective ways. The challenge of the model initialization stage depends on the issue being modeled. For such issues like modelling of student learning styles and cognitive ability there are some standard models in the literature. For instance, in Zatarin, Barron, Camacho and Reyes (2013), four classes of models related to theories of learning styles were identified. The four models are Gregorc model which was presented by Anthony Gregorc and Kathleen Butler. The objective of the model is to provide an organized structure of how the mind works. Four learning styles are identified in the model. Gardner maintains the idea that every student is equipped with

different types of intelligence. Gardner's theory is known as Multiple Intelligence Theory, Nine learning styles are listed in the model. The Myers-Briggs model is known as the Type Indicator Myers-Briggs (MBTI), the model identifies four scales in which it places all subjects. Sixteen types of personality are identified from the combinations of the scales. The Felder Silverman learning style model (FSLSM) was proposed by Richard Felder and Linder Silverman in 1988. The model includes four categories, just like the MBTI model, sixteen different learning styles can be identified in FSLSM. In all, Felder Silverman model seems to be the most appropriate for use in computer-based educational systems (Kuljis and Liu, 2005). To identify learning styles based on FSLSM, Felder and Soloman (1997) developed the Index of Learning Styles (ILS) questionnaire. The main learning style models are summarized in figure 2.5.

However, unlike learning styles shown in figure 2.5, most other kind of models such as student content exploration and concentration, standard models are not visible in the literature. It is therefore more challenging to model exploration and concentration. In the work of Bunt and Conati (2004), it was stressed that modelling of exploration behaviour is more challenging because it is a vague and non-structured activities. Furthermore, it provides only low bandwidth information. The low bandwidth issue relates to the amount and quality of information available to user model (Vanlehn, 1988).

Obtaining sufficient bandwidth information is a great challenge in exploration s model, it is therefore essential to approach it with a well designed interface that will oblige the users to perform some behaviours that can be tracked. The low bandwidth issues further introduce a high level of uncertainty to system users' exploratory model.

Gregorc > Concrete-Sequential > Abstract - Random > Abstract - Sequential > Concrete - Random	Gardner >Verbal-linguistic >Logistical-Mathematical > Bodily-Kinesthetic > Musical-Rhythmic > Interpersonal >Intrapersonal > Naturalistic, and > Existential	Myers-Briggs >Extraversion-introversion > Sensitive - intuitive > Thinking-feeling and > Judgment - Perception	Felder - Silverman >Perception (sensory - intuitive) > Processing (active - reflective) > Presentation (visual - verbal) and > Understanding (Sequential - global)
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Figure 2.5: Main learning style models. (Zatarin *et al.*, 2013)

Furthermore, in Stathacopoulou *et al.*, (2004), it was stressed that because interactive computer systems deal generally with more meagre, vague and haphazardly collected users' data, the information are full of uncertainty. The uncertainty needs to be handled appropriately. The uncertainty can be handled using either numerical techniques or neuro-fuzzy techniques. Numerical techniques were used to manage uncertainty in (Conati *et al.*, 2002).

2.6.6 Information in Student Models

For a student model to be regarded as comprehensive, it is expected to have several kinds of students' information. Some of these information according to Self (1994) include prior knowledge of the domain, learners' progress, preferences, interests, goals etc. All these can broadly be classified into Domain Specific Information and Domain Independent Information. Generally a student knowledge model must be established on the basis of a given domain knowledge structure that is known as domain model. In the domain model structure, the curriculum elements (CE) can be independent or have linked relationship. The commonest relationships are prerequisite and navigation priority. In prerequisite relationship a CE cannot be learnt except when its prerequisite has been mastered and in navigation priority a CE is designated to be present before or after another. Bayesian belief net is an example of the knowledge element network (Binglan, 2001). Other Domain specific information includes Student's prior knowledge about the domain, Records of learning behaviours and Records of evaluation / assessment.

Apart from Domain Specific Information, it is essential for a comprehensive student model to have Domain Independent Information which may include the learning goals, cognitive aptitudes, measures for motivation state, preference about the presentation method, factual and historic data etc.

2.7 Artificial Intelligence Modelling - Soft Computing Approach

Generally, Intelligence is a set of properties of the mind which comprises of ability to plan, solve problems and reason (Jones, 2008). It is the ability to make the right decision given a set input and a variety of possible actions. Though, human has complex intelligence, but intelligence is not peculiar to human, it can be found at lower degree in animals and even in much lower degree in machine. The machine intelligence is known as artificial intelligence (AI). In Jones (2008), the two major approaches to AI are the Neat approaches (also known as the traditional, Top-Down or Good-Old-Fashioned-AI (GOFAI) and the Scruffy approach (also known as messy approach or Bottom-Up approach). Neat approaches are pure and provable. Examples include Decision Trees, Markov Model and Nearest Neighbour learning. The scruffy approaches on the other hands are less provable but still yielding useful and significant result. Neural Networks, Genetic Algorithms, Ant Colony Optimization, Swarm Intelligence and Artificial Immune system (AIS) are some of its examples. The term 'Hard Computing' is used for Neat approaches, while the Scruffy approaches are known as 'Soft Computing'.

Dr. Lotfi Zadeh refocused the attention of AI community to Soft Computing paradigms in 1982. According to him, Soft Computing is the fusion of four fields: Fuzzy Computing, Evolutionary computing, Artificial Neural Networks and Probabilistic Computing. It can also be said to be a fusion of the field of Fuzzy Logic, Neuro Computing, Evolutionary/Genetic Computing and Probabilistic Computing (Ahmed, 2003). What comprises soft computing include Fuzzy sets, Rough Sets, Neural Networks, Evolutionary Computing, Probabilistic and Evidential Reasoning, Multi-valued logic and related fields. The main goal of Soft Computing is to develop intelligent machines and to solve nonlinear and mathematically un-modeled system problems (Zadeh, 1999). Soft Computing is a computational tool that provides approximate solutions to approximated

formulated system. Brief explanations of fuzzy computing and neuro computing that are considered in this study are as follows.

2.7.1 Fuzzy Computing

Fuzzy computing is a soft computing paradigm that is based on fuzzy set, fuzzy if-then rule and fuzzy reasoning. The three main phases are the fuzzification phase, the reasoning phase and the defuzzification phase. Soft Computing system modelling tools that is built on this technique is the Fuzzy Inference System (FIS). The three conceptual components of FIS are the Rule base, the Database and the Reasoning Mechanism. FIS has been applied successfully in the areas of Automatic control, Data classification, Decision analysis, Expert systems, Time series prediction, Robotics and Pattern recognition. It is a multidisciplinary computing paradigms, it is therefore known by other names like Fuzzy – rule – based system; Fuzzy expert system; Fuzzy model; Fuzzy associative memory; Fuzzy logic controller or simply fuzzy system. According to Godjevac (1993), every fuzzy system is composed of four principal blocks. The blocks as shown in Figure 2.6 are Knowledge base - rules and parameters for membership functions; Decision unit - inference operations on the rules; Fuzzification interface - transformation of the crisp inputs into degree of match with linguistic variables; and Defuzzification interface- transformation of the fuzzy result of the inference into a crisp output

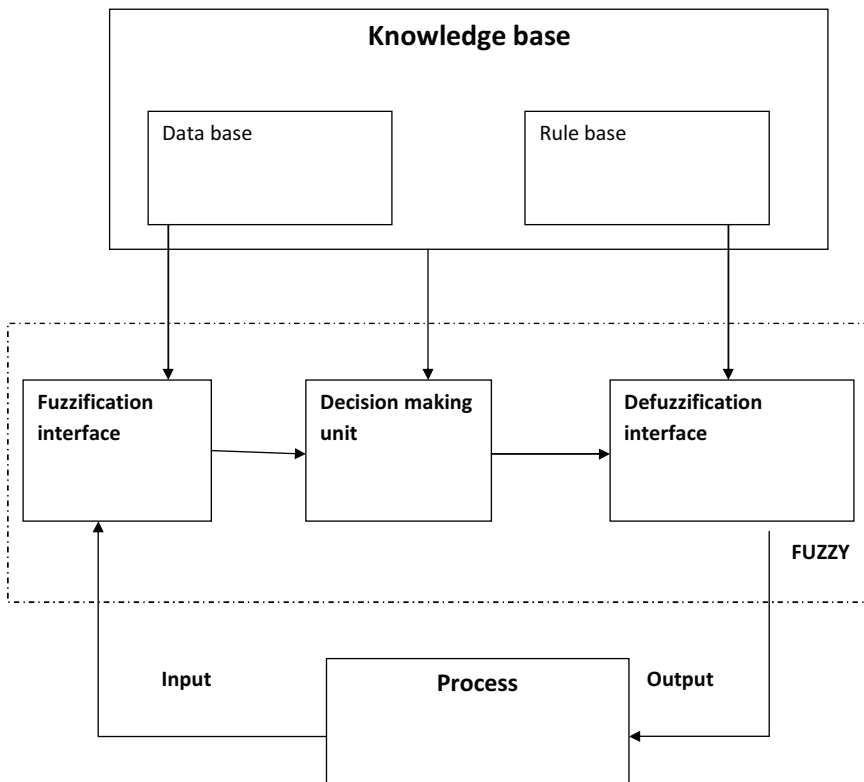


Figure 2.6: General structure of fuzzy inference system. (Godjevac, 1993)

2.7.1.1 Fuzzification Phase

At this phase, linguistic descriptions are used to describe and control processes. Hence, linguistic variable that describe the process state and control processes are formulated, their values are defined in linguistic terms. However, the facts that most observations and measurement are reported in crisp values necessitate the need for the fuzzification phase. Activities at this stage include formulation of fuzzy sets from crisp input and transformation of the crisp inputs into degree of match with linguistic variables via the membership functions.

In Fuzzy sets theory, membership has more than the ‘either-or’ criterion as applicable in the classical set. In the classical, cantor or crisp set membership is either yes/no, true/false or 0/1. A fuzzy set is a collection of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristics) function which assigns to each object a grade of membership ranging between 0 and 1 (Zadeh, 1965). A fuzzy set as in Equation of 2.1 is denoted by an ordered pairs, the first element denotes the element (x) and the second $\mu A(x)$ depicts the degree of membership.

$$A = \{x, \mu A(x) | x \in X\} \quad (2.1)$$

A fuzzy set A in X is a set of $\mu A(x)$ that maps each element of X to a membership value between 0 and 1. It can also be described as a set of x mapped into a membership function ($\mu A(x)$) which has value between 0 and 1. So a fuzzy set $A = \{<x_1, 0.8>, <x_2, 0.3>\}$ implies that x_1 is a member of set A up to 80%, while x_2 is a member only by 30%. The grade membership is a precise but subjective value that is context dependent. Elements of a fuzzy set are taken from a universe they are also context dependent. Methods of Representing Fuzzy Member include Graphical representation for infinite set, Tabular/List representation for infinite set, Geometric representation for finite set and Analytic representations usually an

alternative to graphical method. The fuzzy set theory provided the bases for fuzzy logic.

Fuzzy membership function (MF) is a curve that defines how each point in the input space (Universe of discourse) is mapped to a membership value (or degree of membership) between 0 and 1. It is the function $\mu A(x)$ that ties a number to each element x of the universe. Every element in the universe of discourse is definitely a member of the fuzzy set to some degree down to zero. Membership function can be represented either as continuous or as discrete. In the continuous form, the membership function is a mathematical function. The common continuous membership functions are bell-shaped also known as (π - curve), s-shaped (s-curve), a reverse s-curve (z-curve), gaussian, triangular or trapezoidal. In the discrete form the membership function and the universe are discrete points in a list (vector). Some well known membership functions as expressed in Scarpiniti (2009) are:

$$\text{Triangular membership functions: } \mu(x) = \max \left(\min \left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right) \quad (2.2)$$

$$\text{Trapezoidal membership functions: } \mu(x) = \max \left(\min \left(\frac{x-a}{b-a}, \frac{d-x}{d-b} \right), 0 \right) \quad (2.3)$$

$$\text{Gaussian membership function: } \mu(x) = \exp \left(-\frac{(x-a)^2}{2b^2} \right) \quad (2.4)$$

$$\text{Bell-shaped membership function: } \mu(x) = \frac{1}{1 + \left| \frac{x-a}{c} \right|^{2b}} \quad (2.5)$$

2.7.1.2 Fuzzy Reasoning

Fuzzy reasoning or Fuzzy logical reasoning is the superset of standard Boolean logic. The classical operators are the *min* operation for AND operator, the *max* operation for OR operator and $1 - A$ operation for NOT operator. Scarpiniti (2009) illustrate these operators as follows:

$$\text{Fuzzy Complement: } \mu \bar{A}(x) = 1 - \mu A(x) \quad (26)$$

Fuzzy Union: $\mu(A \cup B)(x) = \max [\mu A(x), \mu B(x)]$ for all $x \in X$ (2.7)

Typically, the fuzzy union operator is specified by a function S

$$\mu A \cup B(x) = S(\mu A(x), \mu B(x)) = \mu A(x)(+) \mu B(x) \quad (2.8)$$

A T-co-norm (or S-norm) is a two place function S (,) satisfying boundary, monotonicity, commutatively and associatively.

Fuzzy Intersection: $\mu(A \cap B)(x) = \min [\mu A(x), \mu B(x)]$ for all $x \in X$ (2.9)

In general, the intersection/conjunction of two fuzzy sets A and B is specified by a function T which aggregates two membership grades as:

$$\mu A \cap B(x) = T(\mu A(x), \mu B(x)) = \mu A(x)(*) \mu B(x) \quad (2.10)$$

(*) is a binary operator for function T known as T-norm (Triangular norm).

A T – norm operator is a two – place function T (,) satisfying: boundary, monotonicity, commutatively and associatively.

Reasoning for fuzzy logic is different from the classical logic because it invalidates Principle of the excluded third $(A \vee \bar{A}) = \text{True}$ and Principle of contradiction $(A \wedge \bar{A}) = \text{False}$ which are two strong hold of classical logics.

Natural and artificial languages have some rules of the type IF *antecedent* THEN *consequent* for representing knowledge and reasoning. In the fuzzy reasoning as well the linguistic variable contained in a rule, are defined by fuzzy sets: if x is A then y is B where:

A and B are fuzzy sets defined on the universe X and Y; the values $x \in X$ and $y \in Y$; the fuzzy rule defined a relation R on the space $X \times Y$. A fuzzy relation is a fuzzy set defined on several domains: $R = X \times Y \times Z \times \dots = \mu R(x, y, z, \dots)$

$$\text{For a binary relation } R, R = A \times B = \mu(x, y) = \min (\mu A(x), \mu B(y)) \quad (2.11)$$

Reasoning can be built on Mamdani and Takagi-Sugeno's forms of rules. The two approaches can be used to specify conditional statements.

For Mamdani rules: IF x_1 is A_1 and x_2 is A_2 and... and x_N is A_N THEN y_1 is B_1 and y_2 is B_2 and ... and y_M is B_M

For Takagi-Sugeno rules: IF x_1 is A_1 and x_2 is A_2 and... and x_N is A_N THEN $y = f_k(x_1, x_2, \dots, x_N)$

In Classical logic, the two fundamental inference principles are Modus Ponens and Modus Tollens, thereby provide the two types of reasoning. For instance, given two domains X and Y and a fuzzy relation R , if A is defined on X and B defined on Y , Reasoning based on classical reasoning can be as follows:

Modus Ponens: Premise: if (x is A) then (y is B) Antecedent: x is $A \Rightarrow$
Consequent: y is B

Modus Tollens: Premise: if (x is A) then (y is B) Antecedent: y is not $B \Rightarrow$
Consequent: x is not A

According to Scarpiniti (2009), the modus ponens from standard logical propositional calculus cannot be used in the fuzzy logic environment for the singular fact that fuzzy is about imprecision while such an inference can only take place if, and only if, the fact or premise is exactly the same as the antecedent of the IF-THEN rule. However, in fuzzy logic the generalized modus ponens is used. It allows an inference when the fact is only partly known or when the fact is only similar but not equal to it.

The Generalised Modus Ponens (for fuzzy logic): Premise: if (x is A) then (y is B)

Antecedent: x is $\hat{A} \Rightarrow$ Consequent: y is $\hat{B}$

$$\mu_{\hat{B}}(y) = \max_x (\min (\mu_{\hat{A}}(x), \mu_{\hat{R}}(x, y))) \quad (2.12)$$

$$[\min (a/c, a/d, b/c, b/d), \max (a/c, a/d, b/c, b/d)] \quad (2.13)$$

2.7.1.3 Defuzzification Phase

The Defuzzification phase converts the set of possible actions into crisp value. The phase is mostly required if the FIS output is not needed to in fuzzy variable. Defuzzification can be achieved through special procedures that select crisp value representative of the fuzzy output. Defuzzification techniques include: centre of gravity (COG), the centre of maxima (COM) the mean of maxima (MOM) and the root sum square (RSQ). Others are the centre of sum (COS) and the centroid or centre of area (COA) (Yager and Filev, 1994).

2.7.2 Neural Computing

The Neural Computing is another soft computing paradigm that has its inspiration in the biological world. Other names for it include Artificial Neural Networks (ANN), Connectionism, Parallel Distributed Processing, and Connection Science. It is a mathematical model or computational model based on biological neural networks (Yashpal and Alok, 2009)

For the fact that concept and implementation are the two ingredients necessary for advancement of technology, Artificial Neurons Networks was conceived as extremely simple abstractions of biological neuron. Hence, neural computation does not have to be the computation carried out by nerve cells. It can as well be realized as elements in a program or perhaps as circuit made of silicon. Though networks of Artificial Neurons has no fraction of the power of the human brain and only a rudimentary understanding of biological neurons networks is known , but it is possible to construct a small set of simple artificial neurons and perhaps train them to serve a useful functions. Some areas that Neural Network has been applied successfully include Function Fitting, Pattern recognition, Data clustering and Time series analysis. (DARP., 1988).

2.7.2.1 Biological Inspiration for ANN

The brain according to Hagan and Demuth (1996) consists of a very large number of highly connected elements called neurons (approximately 10^{11} per element). Each biological neuron is a rich assembly of tissue and chemistry used to facilitate actions. In the biological neural see figure 2.7, functions such as reading, breathing, sighting and thinking are stored in the neurons and in the connections between neurons. Learning takes place as a result of establishment of new connections between neurons or the modification of existing connections. The three principal components of the neurons are the Dendrites, the Cell Body and the Axon. The Dendrites is the tree – like receptive networks of nerve fibers that carry electrical signals into the cell body. The impulses in their thousands from other neurons are conducted via the dendrites into the cell body, thereby causing the neuron to fire. The Cell Body performs the sum and thresholds of the incoming signals and transmits the pulse along the Axon. Axon which is the third component is the 'single long fiber that carries the signals from the cell body out to other neurons. The point of contact between an axon of one cell and a dendrite of another cell is the synapses. When the electrical activity is transferred by the synapses to another neuron, it may contribute to the excitation or inhibition of the target neuron. The occurrence of either is determined by the transmission efficiency of the Synapses, which could be changed to reflect its profitability. The massive parallel structure of biological neurons gives the brain its sensory capability. ANN was built on the principles of biological neurons in terms of structure and parallel operations which make them ideally suitable for implementation on Very Large Scale Integration, optical devices and parallel processors

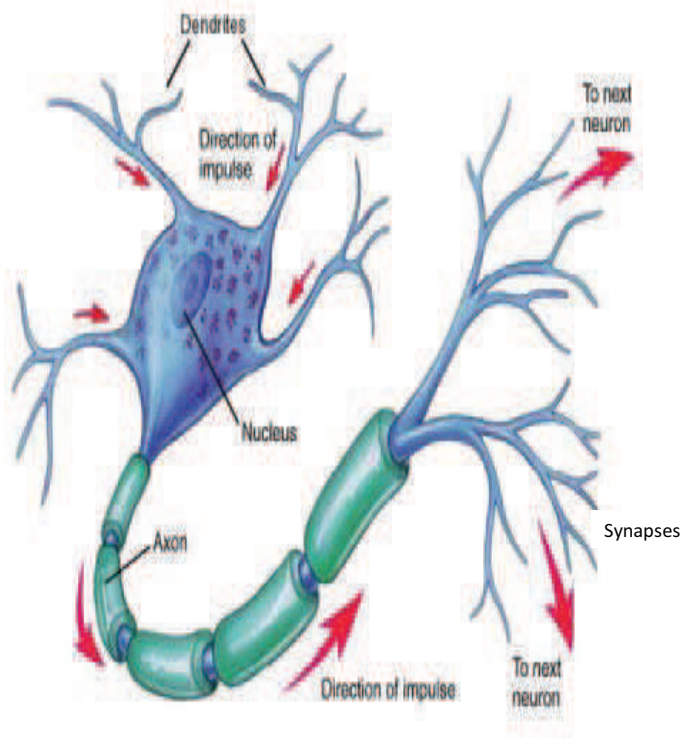


Figure 2.7: A Biological neuron (artificialneurals.blospot)

2.7.2.2 Artificial Neuron Model

Figure 2.8 is a model of a single artificial neuron. Though a typical neuron has more than one input. In the neuron models small italics letters (like a, b, c) represent scalar quantity, vectors are represented by small bold non italic letters (**like $\mathbf{a}, \mathbf{b}, \mathbf{c}$**). Matrices are represented by capital bold non italic letter (like **A, B, C**).

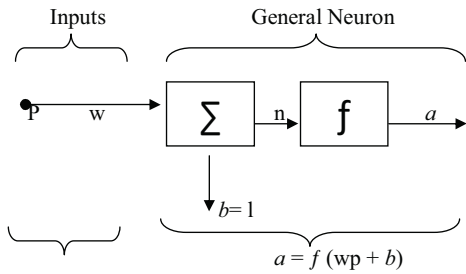
In comparison with Biological Neuron, p represents the input signals into the neuron it will be modified by a weight w which represents the strengths of synapses. $\sum$ and f represent the cell body, the Summer aggregates all the weighted input resulting to n which flows through the transfer functions. The ' a ' represents the signal on the axon.

Typically, the transfer function is chosen by the designer and then the parameters w and b will be adjusted by some learning rule so that the neuron I/O relationship meets some specific goal. b is called the bias, it is more like a w except that it has a constant input of 1, although there could be a AN without bias. w and b are adjustable scalar parameter of the neuron. The three processes that are involved in the simple neuron are:

- i. The weighted function is PW but the distance between the weight and the weight input, $|w - p|$ are sometimes used.
- ii. The net input function is the $\sum$ of the PW (weighted inputs) with the bias, but other operations such as multiplication can also be used.
- iii. The transfer functions: can be any of the standard transfer functions or it could be formulated.

The w and b are both adjustable scalar parameters of the neuron. Adjusting them is known as training of the Network to perform a particular task.

Neuron Model (Single – Input Neuron)



P – Input; w – weight; b – bias (offset)

Σ – Summer; n – net output

f – Transfer function (Activation function)

Figure 2.8: Single Input Neuron (Hagan and Demuth, 1996)

2.7.2.3 Transfer Functions (f)

The Transfer functions are also known as the Activation functions, they are usually used to transform the aggregated input to a desired output. It could be linear or nonlinear function of n . f is always chosen to satisfy some specification of the problem that the neuron attempting to solve. The three most commonly used transfer functions include Hardlimit, Linear and Log Sigmoid. The hard limit is commonly used for the final layer of multilayer networks that are used as function approximation. The Log.Sigmoid is usually used in the hidden layer of multilayer networks, in part because it is differentiable (Hagan and Demuth, 1996).

2.7.2.4 Network Architecture

Neural Network can be built on a single layer or on multiples of layers. Explanations of each type are as follows.

A Layer of neurons

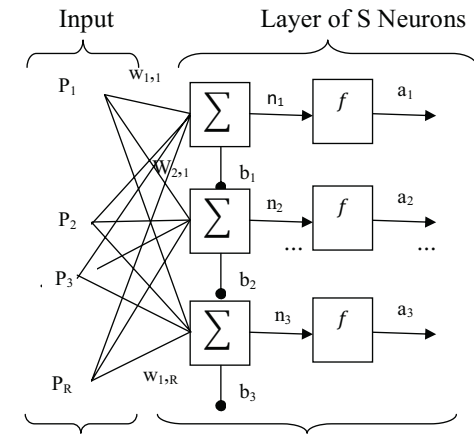
A set of neurons operating in parallel is called a layer. Two or more of neurons can be combined in a layer, and a particular network could contain one or more of such layer.

The layer includes the weight matrix, the summers, the bias vector b , the transfer function boxes and the output vectors. Each element of the input vector P is connected to each neuron through the weight matrix W . The number of layer is appended as a superscript to the variable of interest. It is common for the number of inputs to a layer to be different from the number of neuron. (i.e $R \neq S$). Neurons in the same layer may have different transfer functions. i.e every neuron would have the same inputs and each network would create some of the outputs.

Table 2.2: Activation functions

Name	I/O Relation	Icon	Matlab function
Hard Limit	$a = 0 \quad n < 0$ $a = 1 \quad n \geq 0$		Hardlim
Linear	$a = 0$		Purelin
Log-Sigmoid	$a = \frac{1}{1 + e^{-n}}$		Log sig

The architecture of a single layer network as shown in figure 2.9 is almost completely determined by problem specifications, including the specific number of inputs outputs and the particular output signal characteristic. However, the external problem is not a direct determinant of the number of neurons required in hidden layers. A lot of research is ongoing to determine the number of neurons required in hidden layers.



$$a = f(WP + b)$$

Where

R = number of element in input vector

S = number of neurons in layers

Figure 2.9: A layer of S Neurons (Hagan and Demuth, 1996)

2.7.2.5 Neural Network Design Steps

The Neural Network Design Steps as specified in Matworks (1999) are: Collection of data; Creation of the Network; Configuration of the Network; Initialization of the weight and biases; Training of the network, Validation of the network and Use the network.

The procedure will be to arrange a set of Q input vector as columns in a matrix. Then, arrange the set of Q target vector in to another matrix. The acquired data set is normally divided into three samples which are for Training, Validate and Testing. The default is 70%, 15% and 15% respectively. Standard network for function fitting problem is a two – layer feed forward network with a sigmoid transfer function in the hidden layer and linear transfer function in the output layer. The network is trained using levenberg – Marquardit back propagation algorithm. Training automatically stops when generalization stops improving as indicated by an increase in the mean square error (MSE) of the validation sample. MSE is the average squared difference between outputs and targets. Lower values are better. Zero means no error. Regression R values measures the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

To test the correctness of the network, the Plotting of performance, Training state, Error Histogram, Regression and Fit can be used. Some recommended steps when the Network performance is not satisfactory include retraining, increment in the numbers of neurons or getting a larger training data set. If the performance of the training set is good, but the test set performance is significantly worse – which could indicate over fitting, then reduction of the number of neurons is recommended. If training performance is poor then it may be necessary to increase the number of neurons.

2.7.3 Neuro-Fuzzy Systems

The need to develop adaptive intelligent systems in Scientific and Engineering areas necessitated the fusion of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS). The combined approach has been used most especially in problems where classic techniques do not proffer easy and accurate solutions. The fusion is further necessitated by the inherent strengths and drawbacks of the individual approach. For FIS, the strength among others includes the capability to represent inherent uncertainties of the human knowledge with linguistic variables. Its weakness includes inability to learn from data, inability to generalize and lack of standard topology. The strengths of ANN include learning capability, generalization capacity and standard architecture. Its weaknesses include challenge of functionality interpretation and difficulty in determining number of layers and number of neurons in a system. Weaknesses pertaining to these paradigms according to Abraham (2001) seem to be complementary, it is therefore normal to seek a strong system by combining the two approaches. Learning will be an advantage from the viewpoint of FIS, the formation of linguistic rule will be an advantage from the viewpoint of ANN. Nikam, Nikumbh and Kulkarni (2012) states that a feed forward neural network could approximate any fuzzy rule based system and any feed forward neural network may be approximated by a rule based fuzzy inference system. When the two paradigms are combined they are referred to as Neuro-Fuzzy Systems. The term refers to a system where fuzzy set and fuzzy rules are adjusted using neural networks tuning techniques in an iterative pattern using input, output data vectors. The system in its first phase behaves like a neural network by learning its internal parameters off-line while in the second phase it behaves like a fuzzy logic system by using fuzzy logic and fuzzy rules for inferences. Jose, Fernando and Alexandre (2004).

2.7.3.1 Types of Neuro-Fuzzy Systems

There are several approaches to implementation of Neuro-Fuzzy System. The different combinations of these techniques can be categorized as Cooperative, Concurrent and Hybrid Neuro-Fuzzy System, (Nauck, Klawon and Kruse, 1997). In Abraham (2001), the Hybrid architecture is referred to as Fused Neuro-Fuzzy System.

2.7.3.2 Cooperative and Concurrent Neuro-Fuzzy Systems

In cooperative model, the two paradigms perform their roles in succession in what can be regarded as preprocessing phase and actual processing phase. In the preprocessing phase the Neural Network applied its learning mechanisms to determine the FIS membership functions or the fuzzy rules from the training data. The approximated fuzzy rule or fuzzy set is passed on to the FIS by the Neural Network and the later immediately withdraw to the background while the FIS only is being executed. The working of the Cooperative Neuro-Fuzzy System is as shown with dotted arrows in figure 2.10. The input is preprocessed by ANN and pass onto FIS for it actions and release of output.

On the other hand in the concurrent model, as indicated by the solid arrows in figure 2.10, the ANN work continuously together with FIS in what can be viewed as preprocessing and post processing. This is because the ANN may not only appropriate the input values (fuzzy variable and fuzzy set) but may also interprets the output from FIS especially where the outputs might not be directly applicable to the process. The to and fro arrows across the two models at the start and end of the process reflect the concurrency throughout the process.

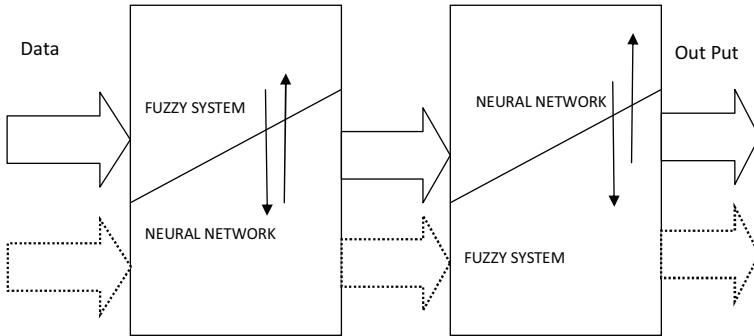


Figure 2.10: Concurrent and Cooperative Neuro-Fuzzy Models

2.7.3.3 Hybrid / Fused Neuro-Fuzzy Systems

In the Hybrid or Fused model, the two models (ANN and FIS) are not maintaining their distinctions. It is no more a case of distinct entities that work concurrently or cooperatively as indicated in figure 2.10. Instead, Hybrid or Fused Neuro-Fuzzy model is represented in a specialized ANN architecture. This is because the conventional ANN learning algorithms (gradient descent) cannot be applied directly to the fuzzed ANN due to the non differentiable functions that are used in the inference process (Abraham, 2001). Applications of differentiable functions in the inference system or using non standard neural learning algorithm are the two possible approaches for handling the challenges. Putting it differently, according to Jose *et al.*, (2004), "Neuro-Fuzzy systems are represented by neural networks that implement logical functions". The representation of fuzzy system through a neural network provides a convenient platform for visualizing the flow of data through the system and the error signals that are used to update its parameters. Neuro-fuzzy system therefore has the advantages of learning through patterns and also easy interpretation of its functionality.

According to Nauck *et al.*, (1997),

"A hybrid neuro-fuzzy system is a fuzzy system that uses a learning algorithm based on gradients or inspired by the neural network theory (heuristic learning strategies) to determine its parameters (fuzzy sets and fuzzy rules) through the patterns processing (input and output)".

The Adaptive Network based Fuzzy Inference System (ANFIS) is a widely used neuro-fuzzy model. It is a fuzzy based model formulated by Jang (1997). It could be described as a five layer network as shown in figure 2.11 or as a six layer network when the crisp input layer is considered to be the layer 1.

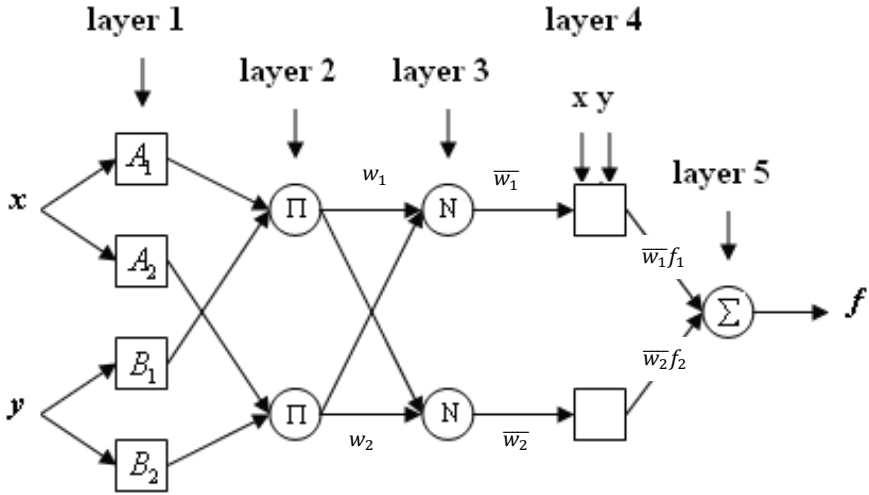


Figure 2.11: Adaptive Neuro-Fuzzy Inference System (ANFIS) Model.
(Al-Hmouz et.al., 2012).

The ANFIS model in figure 2.11 has two input x, y with the input terms A_1, A_2 for the former and B_1, B_2 for the later. If the FIS under consideration is a first order Sugeno fuzzy model then the following two fuzzy if-then rules can be set.

Rule 1: if x is A_1 and y is B_1 , $f_1 = p_1x + q_1y + r_1$

Rule 2: if x is A_2 and y is B_2 , $f_2 = p_2x + q_2y + r_2$

The reasoning mechanism for generating f in Sugeno Fuzzy can be written as

$$f = \frac{w_1}{w_1+w_2} f_1 + \frac{w_2}{w_1+w_2} f_2 = \overline{w_1}(p_1x + q_1y + r_1) + \overline{w_2}(p_2x + q_2y + r_2) =$$

$$(\overline{w_1}x)p_1 + (\overline{w_1}y)q_1 + (\overline{w_1})r_1 + (\overline{w_2}x)p_2 + (\overline{w_2}y)q_2 + (\overline{w_2})r_2 \quad (2.14)$$

It can be deduced from these that when the values of the premise parameters in layer 1 are fixed, the overall output can be expressed as a linear combination of the consequent parameter in layer 4.

ANFIS hybrid learning algorithm comprises of forward pass and backward pass. In the forward pass node output values go forward until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the output error is propagated backward and the premise parameters are adjusted by gradient descent method.

The following are other models of hybrid neuro-fuzzy systems, they are all built on the same principles as in ANFIS but different only in their approaches.

- i. Fuzzy Adaptive Learning Control Network (FALCON).
- ii. Generalized Approximate Reasoning based Inference Control (GARIC).
- iii. Neuronal Fuzzy Controller (NEFCON).
- iv. Fuzzy Inference and Neural Network in Fuzzy Inference Software (FINEST).
- v. Fuzzy Net (FUN).
- vi. Self Constructing Neural Fuzzy Inference Network (SONFIN)

- vii. Fuzzy Neural Network (FNN).
- viii. Dynamic/Evolving Fuzzy Neural Network (EFuNN and dmEFuNN).

2.8 Review of Related Works

Generally, formulation of E-learning specifications, standards and reference models are guided by the intention of the standard body, they are suitable only for their intended purposes. They are usually incomprehensive, restrictive or vague for other aspects of E-learning. Consequently, several efforts have been made by researchers to build and implement E-learning frameworks and architectures that leverage fully or partially on the existing E-learning standards. Some of the efforts are reviewed as follows.

2.8.1 Using E-learning Standard as Basis for Application Profiling

Standards are available for several aspects of E-learning like metadata, content packaging, learner information, communication and system conceptualization. However, all of these standards are only meant to serve as bases but not as a blue print for E-learning applications. Hence, the profile of a typical E-learning application can be customized on a chosen standard, extension of a particular standard or combination of several standards, (Robert and Timothy, 2009). Abound in the literature are several E-learning frameworks, architectures and models that are based on these approaches. Researchers have also proposed and even implemented several techniques for E-learning content. The following are discussions of some works on formulation of E-learning frameworks, architectures and models based on existing E-learning standards.

In Recker and Wiley (2001) it was noted that the IEEE Learning Object Metadata (LOM) standard's form of prescriptive metadata doesn't provide enough information to adequately support the learning process. A typical instance stressed

is the provision of school, higher education, training as the only prescribed values for Context metadata field. These values according to them are neither comprehensive enough to cover all possible learning context nor descriptive enough to depict their peculiarities (Vladan, Jelena, and Dragan, 2007). Another limitation of LOM is that it is too author dependent, at its best, it only provides authoring context and intended use of the learning content as perceived by the author at the point of designing. But because the author may not be able to capture all applicable contexts, so the metadata can never be comprehensive enough to even describe the learning context of the learning object less covering the learner's context and learning goals.

Karagiannidis, Sampson and Cardinali (2001), criticize the existing content packaging specification, which is of 'table of content' structure. That, it only enables re-use of learning materials but has no provision for re-use of adaptive learning materials. The limitations are traceable to the constraint of the applicable standards. The work present an architecture which aimed to facilitate the definition of adaptive educational e-content by extending the manifest XML file of each content package. It extends the adaptation rules to include the necessary information for selecting learning objects for different learner profile. Their work was particularly based on the European IST Knowledge on Demand project (KOD). According to KOD, description of adaptive educational e-content should include the definition for the concept ontology, the learning resources, the competencies, the questions and tests, the user profiles and the navigation rules. The KOD project definition therefore enables a packaging of knowledge rather than content as in IMS.

Corbiere and Choquet (2002), stressed that currently, all the resource's pedagogical, educational, ergonomical or technical characteristics are constrained by the existing elements and vocabularies classifications as dictated by the content

packaging data structure and platform architecture. That the two major roles of a teacher (as a tutor/teacher and as author/designer) have been desynchronized in Information and Communication Technology (ICT), the tutor/teacher role is well represented in the LTSA and it is continuously been perfected, however, the same cannot be said of the author/designer role. This issue therefore calls for a re-engineering of the current distance learning architecture. The research describes an architecture centred on a component model for the course cycle. It is a model re-engineering that incorporates the class itself, the pre-class and the post-class operations. It is based on the LTSA, LOM and Education Model Language (EML). It is to bring about the operationalization of the course's progression and to provide a framework for the evaluation of usage scenarios. To accomplish this, the LTSA's level 1,3 and 5 were modified. The <design> process was introduced at the general category, and to widen the spectrum covered by the initial LTSA model. The new components allow the analysis of the flow of information linked to the LTSA by carry out analysis functions of the data exchange between Delivery, Evaluation and Coach Processes. The designer specifies in the learning scenario those tasks that are carried out during training session which include collecting digital tracks, converting to information and taking decision. A new component model in terms of information flow was defined for the re-engineering process.

The work of Xiaofei, Abdulmotaleb and Nicolas (2003) explained that, though, there are several proposed standards for content standardization and components models. But there is a lack of an implementable architecture to define how to combine the information models. According to them, currently, E-learning systems built on different platform are not truly interoperable. For instance, E-learning systems built on Microsoft COM are not interoperable with OMG CORBA. As their contribution, they came up with an original proposal for a functional architecture to build standard driven distributed and interoperable

learning system. The design was based on ADL SCORM and SUN Microsystems functional model. The SCORM's LMS was divided into LCMS and LMS for clarity, standard information interchange based on but not limited to SCORM content model were defined, finally, Web Services Technology was used to implement the interoperability between the LMS and LCMS. Brusilovsky (2003) also asserted that the current Adaptive Learning Environment (ALE) that support adaptive course delivery require additional level of information about the entities that make up a course.

Siqueira and Melo (2003) formulate E-learning environment based on framework composition. The approach used was by expanding a "semi-complete" framework using a mechanism for components configuration. The components of the framework include data and metadata management, groupware management, content development management, assessment and evaluation management, interface management, role and security management, and rule management.

The sufficiency of the existing E-learning standards to facilitate and support the introduction of adaptive techniques in computer-based learning systems was investigated in (Alexandros and Susanne, 2004). It was discovered that in terms of domain modelling, that is modelling of course or learning related activities, the existing E-learning standards do not suffice to capture the rich semantic structure that underlie static learning materials. Furthermore, they explained that the dichotomy between the literature research (prototype) and actual commercial E-learning system in compliance to adaptivity is largely due to insufficient support for adaptive behaviour in existing E-learning standards.

Sabir (2004) mapped the structure of an ideal Intelligent Tutoring System (ITS) to the components of SCORM, and proposed Architecture of a functional model of an ITS. The work showed that the User interface, Student, Tutoring and Expert modules of the ITS can be modeled effectively in the SCORMs Content

Aggregation Model (CAM). The CAM consists of the Metadata, Content Packaging, Sequencing and Navigation components.

In Li and Chang (2005), a personalized E-learning system which can automatically adapt to the interests and levels of learners was design. The system was designed based on IEEE Learning Technology System Architecture (IEEE LTSA). The LTSA learning resources were represented as Web pages (pg). The pages were organized by the topics and structured in Ontology Knowledge Based. The LTSA's Learner's Record was implemented by User Profile, that stores information such as performance and preferences. The Evaluation Entity was implemented by Feedback Extractor which applies the information fusion techniques to infer learner's preferences from multiple feedback measures. LTSA's Delivery Entity was implemented by Learner Client, and finally the Coach Entity was implemented by User Profiler which interacts with User Profile and other components to deliver personalized information using the collaborative filtering algorithm. A prototype of the system was developed and evaluated with explicit ratings of the reading time, the scroll and the print & copy view. The work is a demonstration of a system formulation based on existing E-learning standards.

In the work of Karampiperis and Sampson (2005), the research and developmental efforts made towards web-based educational systems that are tailored to specific pedagogical approached were extolled. However, the importance of sharing and reusing learning activities among Learning Management System was stressed. Learning activities were defined as a triple containing the learning content, the actors and their corresponding interactions. The interactions can either be with the learning content, with the educational environment or between the participating actors. In the work, it was established that the current state-of-the-art learning systems such as Blackboard, WebCT, Lotus Learning Space, learn eXact and so on cannot handle learning activities effectively. The

reason adduced to this assertion is that they are all LTSA standard conformant, and that the LTSA itself does not support learning activities structurally. For instance the interaction between the learners that was abstracted in layer 1 did not indicate how such interaction is supported by the system. To ameliorate these limitations, the ADL SCORM refines the IEEE LTSA reference architecture by specifying missing interactions. The limitations of the SCORM based authoring tools however include the fact that they are based on a "single learner model", the learning activities are content based and there is no provision for learning activities interoperability. To this end, a high-level architecture for authoring of learning activities that combines the components of a SCORM compatible authoring system with the Learning Design framework was proposed. Its main components include; the Learning Design subsystem, Content Packaging subsystem and Learning Resources Metadata Authoring & Management system. The learning Design and the Content Packaging sub-systems were implemented as an integrated tool, referred to as ASK_LDT. The tool is based on IMS Learning Design Level B, and is available online from www.ask.itl.gr/demos/ASK-LDT_vUF_rel1.1_Setup.exe. This work demonstrates a technique of extending SCORM for content and scenario packaging.

Hyunjong and Taeyoung (2005), explained that the two major components suggested by Mental Model in Cognitive Psychology are knowledge structure and processes for using this knowledge. Thus, a major concern in instructional design is the representation of subject contents to facilitate learning. Most studies have focused on the pedagogical aspect of E-learning system but they have not provided sufficient guidelines for E-learning designers. To this end, the duo in their work, model the subject content structure which is the structural knowledge in a mental model. The approach they used includes enhancing LTSA with Adaptive Sequencing Plan and Ontology-based contextual knowledge. The Data structure

diagram and the UML collaboration diagram of the proposed model were presented.

Similarly, Sengupta, Chaki and Dasgupta (2009) analyzed IEEE-LTSA has been too abstracted to be adapted by Learning Management System (LMS) developers in a uniform manner. Consequently, several attempts made in the literature to improve E-learning for pedagogical and content delivery efficiency were discuss. However, the identification of specific requirements for individual learners of vastly different background and the design of effective LMS remain a challenge. Design of an implementable Learner's Quanta (LQ) based efficient and adaptive learning system based on LTSA but augmented with hybrid model learning (contact and distance learning), two mode evaluation (assignment and objective test) and counseling was made. In the work, UML, Sequence and Activity diagrams were used to demonstrate a learner's Quanta approach to the design of a Person-centric delivery system from a large pool of LQs. Learner's Quanta (LQ) refers to a Learner's Quantum of study which is a measured part of a topic with a specific output objective requiring a specific input knowledge on the part of the learners. The system has an inbuilt mechanism to automatically refer a learner to a contact learning mode if such students fail to achieve the expected level of knowledge after several attempts in the E-learning mode.

Robert and Timothy (2009) in an attempt to enhance the capability of Learning Object Model (LOM) in the areas of pedagogy, adaptive learning and learning assessment demonstrated the application of the three predefined methods to extend SCORM as specified in the ADL guidelines. The recommended approaches are; by adding new metadata element, by adding new vocabulary for element and by references to an internal and external XML files using the location element.

Kumar, Samaddar, Samaddar and Misra (2010) perform a step-wise extension of IEEE-LTSA E-learning architecture to a secured Client-Server based

model and then to a distributed system based model with added security features. Furthermore, an extended E-learning architecture in service oriented architecture (SOA) was proposed which is capable of providing secured stand alone as well as composite teaching-learning services. The developed model was tested with a case study of an E-learning web portal to prove the validity of the proposed extended architecture.

Summarily, the reviewed related works show that the existing E-learning standard may not exactly fit for some kind of architecture and implementation. It is however instructive to use the existing standard as basis for any E-learning initiatives for interoperability and reusability. To this end, adequate extensions to existing standards are appropriate and legal because provisions are made for such by the standard bodies.

The literature also revealed that most modelling and architectures focus on content preparation, packaging and presentation. They largely provide quality assurance for the "Teaching" component of education – they are teacher centred. However, attention of the E-learning community needs to be drawn to how to device strategies to monitor learner exploratory behaviour and provision for support services. Hence, it is essential to provide not just quality assurance for the "Learning" but quality enhancement as well.

Furthermore, it is deduced from the literature that some techniques grounded in theories of education suggest active learning approach for teaching. These approaches such as Gagnes model guaranteed learning when used correctly especially for learning design. Adopting activity driven E-learning model will require reengineering of some E-learning standards. The traces of the users in the log file needs to be tracked as a measure of learner's participation which is a strong indicator for performance.

2.8.2 Student Modelling Using Probabilistic Approach

In VanLehn (1998) various assessment systems that are based on Bayes classification algorithm for students modeling were evaluated. Bayesian is a popular uncertain classification model. The main weakness of this model is that the teacher needs to describe classification in terms of conditional probabilities. However teachers naturally do not classify students in probabilistic pattern, the classification model is therefore too complicated for end users and complex to inspect.

Bunt and Conati (2004) use Bayesian Network built on iterative design and evaluation process to model students' exploratory behaviour in open learning environment. It is an advancement on their earlier work in which an Adaptive Coach for Exploration (ACE) was built. The four modules in ACE are A GUI, A knowledge Base, A Student Module and A Coach.

In the work, open learning environment was viewed as an alternative to the traditional tutor-controlled, computer-based, educational systems. Open learning environment places less emphasis on supporting learning through explicit instruction, restricted set of activities under the supervision of a computerized coach as in traditional tutor controlled educational system. Instead, open learning environment provides the learner with an opportunity to learn through free exploration of the instructional domain. Learner explore by actively engaging in activities supported by the environment's interface. These activities often involve simulations where learners can experiment with different aspects and parameters of a given phenomenon in order to observe the effects these changes have on outcomes of the simulation. The whole idea is that through performing a meaningful set of experiments and by generalizing the results of these experiments, learners can acquire deeper and a more structured understanding of concepts in the domain than they would from a less active style of learning.

However, several studies have shown that most often open learning environment do not achieve the expected learning objectives. Its success strongly relies on a number of user-specific features and on the extent to which the open learning environment allow learners to practice and acquire the meta-cognitive skills associated with effective exploration. Some of these skills include hypothesis formulation, the ability to construct meaningful experiments, self-monitoring and self explanations. The user-specific features include the learner's activity level, possession of the meta-cognitive skills, general academic achievement and cognitive ability.

2.8.3 Student Modelling Using Fuzzy Logic, Neural Network and Neuro-Fuzzy Models

Stathacopoulou, Magoulos and Grigoriadou (1999) developed a well defined framework for neuro-fuzzy students modelling of cognitive ability in Intelligent Tutoring Systems. The blocks in the model are input, relation, aggregation and output blocks. While fuzzification and defuzzification were implemented in the input and output blocks respectively the fuzzy inference was implemented in the relation and aggregation blocks. The Stathacopoulou approach works but it is computationally intensive.

Sadique, and Ashok (2005) tested ANFIS with their rule and got satisfactory result. The major weakness of ANFIS is that it uses the Sugeno type of fuzzy inference. This result is in variance with the position of Marian (2002) in which ANFIS was recognized as the first rule-based neuro-fuzzy systems for function approximation but not recommended for applications where interpretation is required.

Neuro-fuzzy model was used to model students academic performance based on test score and test completion speed in Sevarac (2006). The choice of the model

was due to the facts that the information gather about the students through communication channels (keyboard and mouse) is very restricted. While those from teacher's direct observation are imprecise, error prone and its interpretations are vague and uncertain. In the work, four level feedforward neuro-fuzzy network structures were proposed. The four levels were input, fuzzification, premise layer and the output layer. Fuzzy set was defined for student's score and speed. Appropriate rules were formulated to reflect experts reasoning. The input were the test score, test time, number of correct or wrong answers and number of times students reviewed lesson. The network was trained using least mean squares algorithm to classify the students as Bad, Good, Very good and Excellent.

In the work of Asteriadis, Tzouveli, Karpouzia and Kollias (2008), biometrics techniques were used to detect the facial feature of the user in front of a computer monitor via the webcam. Base on the head movement and the eye areas, the head pose and the eye gaze were estimated. Furthermore, mouth opening, eyebrows, frowning, hand movement and distance change of the user from the screen are estimated and monitored. All these features are fed as input into Attention Estimation module that was designed as a Neuro Fuzzy Inference System to infer the behavioural state of the user. Consequently, the users' behavioural states were classified as Frustrated, Distracted, Tired/Sleep, Not paying attention, Attentive or Full of interest. The face is detected using the Boosted Cascade Methods, the noisy image was post processed using ellipse fitting algorithm. The detected biometrics of the user is used to determine the user profile and adapt the provided multimedia presentation to the current user needs. The research is in the category of Affective computing, it is built on the Theory of Mind (TOM). TOM reveals the principle and techniques that human deploys in other to understand, predict and manipulate the behaviour of others, TOM can be used to anticipate or manipulate the behaviour of a user or an agent.

Lin, Chen and Tsai (2008) noted the Maximum Likelihood Estimation (MLE) and Bayesian Likelihood Estimation (BLE) techniques for examinee ability estimation paid little attention to inconsistencies that may exist between response items and examinees ability. They therefore presented a novel learning ability model using Adaptive Network-Based Fuzzy Inference System (ANFIS). The model can adaptively choose questions based on the item response theory in accordance with the ability estimation for the examinees. The experimental result shows that ANFIS has a good inference capability whenever the test information is high.

The evaluation methodologies for the e-learners that will be a feedback to the decision makers in E-learning system was introduced in Hogo (2010). In the work the Learner's profile plays a crucial role in the evaluation process to improve the e-learning process performance. The e-learners based on their behaviour were clustered into categories. The categories / classes were named as regular, workers, casual, bad and absent. The work presents the use of fuzzy c-means and kernelized fuzzy c-means clustering techniques to find the learners' categories and predict their profile. The phases employed are data description, preparation, features selection and the experimental design. The analysis of the obtained results and the comparison with the real behaviour of those learner proved that there is a match of 78%.

A Fuzzy Expert System (FES) for student academic performance evaluation was proposed in Ranjeet and Vijendra (2011). The work revealed a difference in outcome between the classical and the developed fuzzy logic based expert systems methods. While the classical method adheres to a constant mathematical rule, evaluation with fuzzy logic has great flexibility and reliability. It was concluded that student performance evaluation using fuzzy logic is suitable not

only for laboratory application, but also for student performance evaluation in any educational domain.

The advancement in mobile technology has made it possible for learning activities to occur everywhere in what is known as m-learning. To this end, Al-Hmouz, Shen, Al-Hmouz and Yan (2012) developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for delivering adaptive learning content to mobile learners. The ANFIS model was designed using trial and error based on various experiments. The study was conducted to illustrate that ANFIS is effective with hybrid learning, for the adaptation of learning content according to learner's context scenarios. The performance of the ANFIS model was evaluated using standard error measurement which reveals the optimal setting necessary for better predictability. The MATLAB simulation results indicate that the performance of the ANFIS approach is valuable and easy to implement.

In the work of Yildiz, Bal and Gulsecen (2013), a mathematical model was developed to predict distance education students' year-end academic performance using the first eight weeks data on the learning management system. The students models were constructed on three techniques namely; the classical fuzzy model, the expert fuzzy model and the gene-fuzzy model. The data of 218 students were collected and used for comparing the performance of the three models. It was concluded that the most accurate of the three models is the gene-fuzzy model, while the least is the classic fuzzy model.

In Akinnuwesi, Uzoka, Olabiyisi and Omidiora (2012), the capability of Neuro-fuzzy model to handle complex scenarios was demonstrated. In the work, a Neuro-Fuzzy Quality of Service (QOS) model was built. The model matched the organizations/ user variables with Distributed Software System Architecture (DSSA) evaluation factors. The user-centric model is a paradigm shift from the

common machine –centric models that could not match organizational variables with DSSA components.

2.8.4 Learning Activities Tracking and Presentations

Tracking users' activities in computer application is a common feature. The essence could be for improved customer care, for mining or building recommender systems (Hijon and Carlos, 2006). The prominent usage of E-learning system has prompted many researchers into investigating approaches for tracking user's traces logged into various tables in the LMS database. The intention is to actualize learning analytics as bases for support. Highlights of common approaches are discussed as follows.

May, George and Prevot (2007) established the importance of Computer Mediated Communication (CMC) tools in facilitating communication between actors in distance learning. The research investigated the methodological challenges involved in designing and developing a generic system for tracking user's activities in discussion forums. The suggested approach builds a Web-based system architecture, which is composed of client side and server side trace collectors, trace manipulation procedures, trace repository, trace analysis and trace visualization.

A Weblog Analysis Tool (WAT) which allows educators to describe activities from sequence of meaningful website interactions was developed in Jason, Judy and Grant (2007). Learning activity was identified as series of interactions within a website to achieve a particular outcome. The online learning activities were categorized as presentation, organizational, explorational, goal-focused and complex activities. The analysis techniques used to gain information about learning behaviour include the completion rates, length of activity, frequency and length of sequence, and unusual or outlying results.

In the work of Florian, Glahn, Drachster, Specht and Fabregat (2011) activity based learner model was developed. The model aimed at providing competence assessment, teaching/learning support and recommendation. The model strengthens activity-based learner assessment over outcome-based assessment. The model was implemented based on Activity Theory Model and Actuator Indicator Model to have a flexible and extensible interface to moodle tracking data for different roles in learning processes. In the model the indicator layer shows smart indicators for the input from the control layer.

Lack of suitable e-learning user's behaviour model that can be used to make a prediction for learning outcomes or performance in open source E-learning system (like Moodle) was established in Chayanukro, Mahmuddin and Husni (2012). The study therefore developed a generalized E-learning usage behaviour model. It is a user classification model implemented using Support Vector Machine (SVM). Several important moodle table were identified. The group of web log attributes processing used are count, time and score. Other steps involved are data preparation, data extraction and model verification. The weaknesses of the approach among others include the fact that SVM is a poor classifier of high dimensionality features.

Student Activity Meters (SAM) that visualizes learner actions was developed in Govaerts, Duval, Verbert and Pardo (2012). The model is to facilitate awareness and self reflections on the part of the learner. The methodology was based on metrics such as basic time spent, resources used, forum view and post actions. The evaluation was done by a task based interview using the think aloud protocol as a means of providing insight into learn-ability, errors and efficiency.

Conclusively, it is deducible from the literature that IEEE-LTSA is a prominent E-learning system conceptualization standard that is open for adoption and extension towards actualization of E-learning initiatives. The literature also

revealed that the softcomputing approaches to system users modeling appears favourable than the probabilistic approaches due to the formers capability to accommodate uncertainty with less complexity. Furthermore, tracking of user's activities on electronic platforms is gaining popularity. The intent among others is to build recommender systems and personalized systems. To this end, this research extends IEEE-LTSA with learning design subsystem and neuro-fuzzy learner model.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Architecture for Learning Activity Driven E-learning System

The formulated learning activity driven e-learning architecture comprises of the abstracted components, vocabularies and information flows in IEEE-LTSA and SCORMS-LMS. The IEEE-LTSA is used because it articulates the functional components for a standard E-learning system, and thereby provides a very clear fundamental architecture for LMS. However, the one way information flow specified in the architecture is hereby modified to facilitate activities driven e-learning system. The new architecture adopts but modifies all the stores, all the processes and some of the flows in IEEE-LTSA to reflect the new initiative. Furthermore, it adopts the two components approach to e-learning system proposed in SCORM. Thus, the formulated architecture for the Learning Activity Driven E-learning System is a fusion of “the learning design and packaging architecture” and “the learning activities delivery and monitoring architecture”. In addition, the implementation of the model adopts service oriented architecture proposed in SCORM. Detail descriptions of the two components are as follows.

3.1.1 The Learning Design and Packaging Architecture

The Learning Design and Packaging Architecture (LDPA) abstract the teachers-end component of the architecture. It is a multi-roles learning design and packaging platform for development of Learning Design Management System (LDMS), its overview is shown in Figure 3.1.

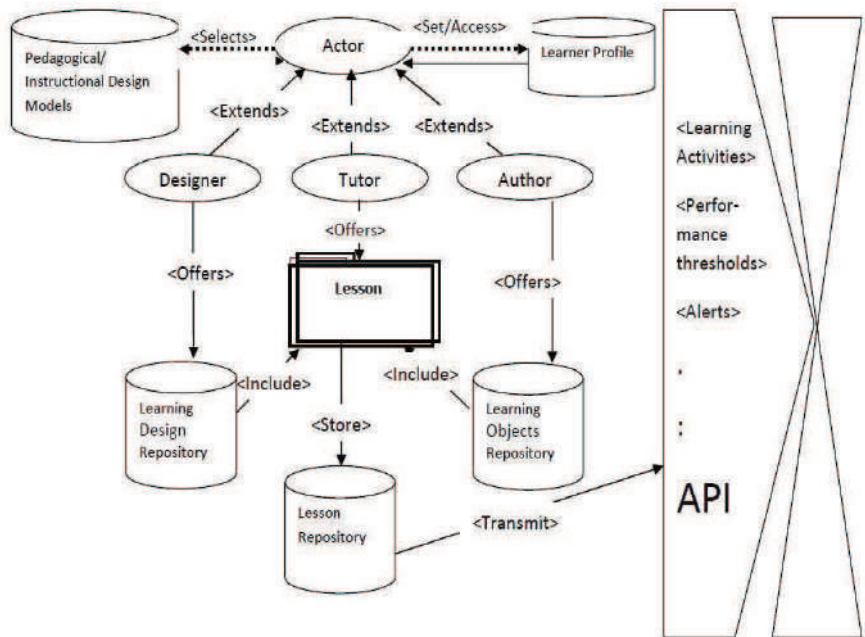


Figure 3.1: The Learning Design and Packaging Architecture (LDPA)

In Figure 3.1, the three actors identified for e-learning lesson design are the lesson designer, the content author and the tutor. Activities of the trios require accessing and understanding the learner information. This is depicted in the figure with the information link 'Actors - *Set/Access* - Learner profile'. Similarly, they need to have the lesson objective and domain in mind as depicted in 'Actors- *Selects* – Pedagogy/Instruction Design'. Content authors are to use relevant content authoring tools to create contents or SCOs as the case may be. A lesson tutor formulates a unit of learning (a course or a lesson) by making appropriate choice from collections of Instructional design models, learning design and learning objects. When all that are required are found in the repositories the tutor may not need to reinvent the wheel by building his/her own contents. The tutor would only be required to sequenced learning activities appropriately and set performance evaluation rules to be used by the Neuro-fuzzy model. When satisfactorily done, the lesson is saved in the lesson repository for learners to access via compatible delivery and monitoring system or LMS. Provision for 'Alert' is made to signify to the learners and other stakeholders via e-mail or mobile phone that a new lesson or module is ready for attention.

3.1.2 Pedagogical Grounded Instructional Design

A Course or unit of learning (UoL) is the product of Instructional Design. In this study, CSC 306 titled System Analysis and Design was packaged using the extended Moodle platform. Unlike the default course packaging platform, in this case, the tutor is carefully guided by series of steps as contained in the instructional design model selected. Activity diagram for a typical unit of learning is as shown in Figure 3.2.

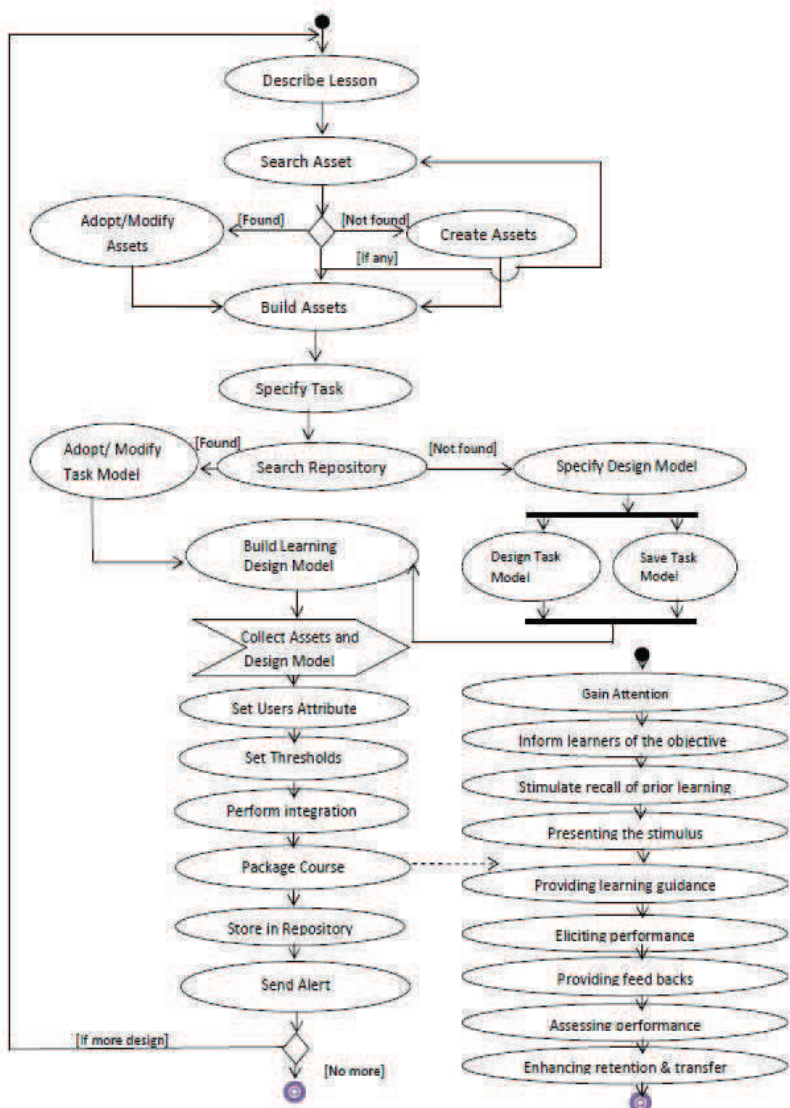


Figure 3.2: Activity Diagram for Instructional Design Grounded in Gagne

The diagram in Figure 3.2 demonstrates a case for Gagne instructional design model. The diagram depicts that the tutor needs to specify the objective or the purpose of the lesson by 'Describing the lesson'. All assets considered to be necessary must be collected or built. If such assets are found in the repositories they can be adopted or adapted to suite the intended lesson. Having collected all required assets, the next action is to specify the tasks which inform the choice of learning design model. The intended model can be searched in the repository, if exact model is found it can be adopted otherwise some form of modification may be made or a new model may be created and save in the repository. The collected assets and services will be integrated into the design model. Performance thresholds will be set and the course will be packaged and store in the lesson repository. Finally alert may be sent to stakeholders to announce the creation of the lesson.

3.1.3 Moodle and LDPA Integration

Moodle is a platform built on three-tier architecture. The first tier is the Database (backend) layer that consists of over 200 tables. It is commonly deployed using MySQL Database Management Systems (DBMS) though it is compatible with several other DBMS such as Oracle and SQLServer. The choice of MySQL for Moodle deployment is significantly informed by the fact that the duo of MySQL and Hypertext Pre-Processing (PHP) programming language are open-sourced. The second tier is the application processing (middle) layer. It consists of PHP modules in their hundreds, each one of them performs specific functions. The third architectural level in Moodle is the GUI- Graphical Users Interface (Frontend) tier. The interface serves as the platform for interaction between the users and Moodle. The interface was built using HTML, JavaScript and JQuery languages. In view of these, the integration of the learning design and packaging architecture in Moodle

is accomplished by extending the three tiers of the architecture. The details are as follows.

3.1.3.1 The Database (1st Tier / Backend) Extension

The backend was extended by creating eleven (11) additional tables. The names of the tables are pedagogytb, pedstepstb, tblessonconst, tbsetthreshold, tbthreshold and transformedtb. The remaining tables are temp_input, temp_input_disp, temp_list, temp_output and temp_output_disp. The pedagogytb is the system name for pedagogical table. It is a table with three (3) attributes; the primary key is the pedagogy identification number (pedid). The primary key for the pedagogy steps table (pedagogystepstb) is the combination of pedid and the pedagogy process steps; it has three (3) attributes in all. The Lesson construction table has four (4) attributes; its composite primary key is made up of lessonid, pedid and period. The tbsetthreshold has seven (7) attributes; its composite primary key is made up of lessonid, period, stepnum and stepevent. The tbthreshold has seven (7) attributes with thresholdid and lessonid as the primary key. The transformedtb has nine (9) attributes out of which transformid and lessonid form the composite primary key. The Data model for this core extension is as shown in Figure 3.3. Other complementary tables are temp_input, temp_input_disp, temp_list, temp_output and temp_output_disp. These tables are temporary table used by the Learner Activity Evaluation control panel.

Relationships for learning_activitiesdb

22 August 2014

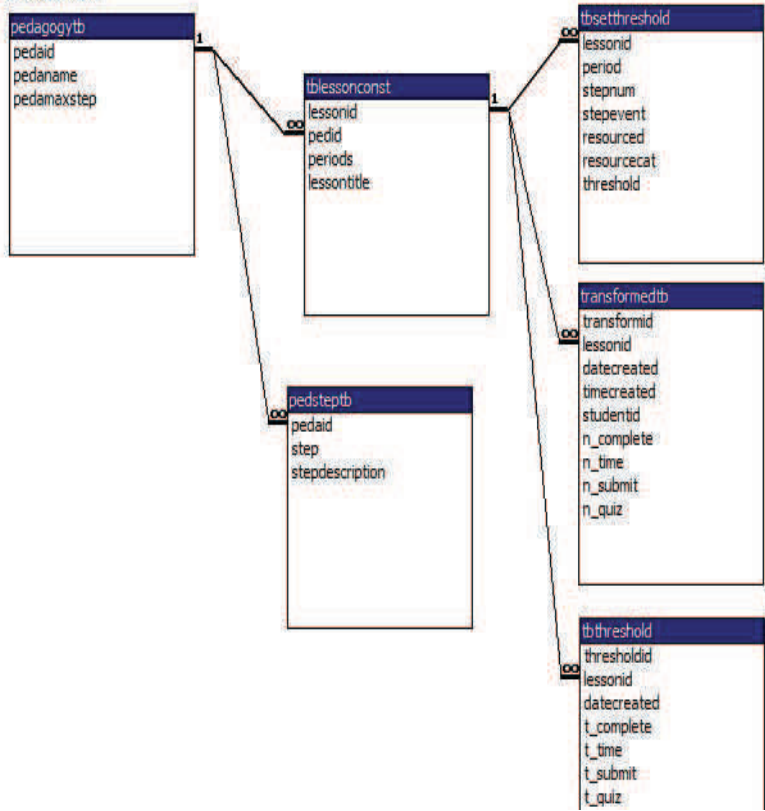


Figure 3.3: Data Model for Learning Design and Packaging

Figure 3.3 illustrates the six (6) tables that extend the Moodle database. It illustrates the interactions between six out of the eleven table in one (1) to many (∞) relationships. The integrity of the model is ensured by the activation of its referential integrity. By this, only existing lesson id can be referenced as foreign key.

3.1.3.2 Application Processing (2nd Tier / Modules) Extension

Combinations of HTML, PHP and Ajax where used to develop relevant modules for data collections and manipulations. The modules for the pedagogy table are save_ped, search_ped and next_ped. Table pedstep's modules are save_pedstep, search_pedstep and view_all_pedstep. For the tbsetthreshold, the modules are save_lesson_threshold, delete_lesson_threshold, view_lesson_threshold and view_threshold_summary. Lesson construction table has modules for estimating completion, participation, scores and time. Details of these modules are as contained in appendix A.

3.1.3.3Interface (3rd Tier / Frontend) Extension

The pedagogies tips can be accessed by lesson tutors via the 'Pedagogy Interaction Modules' link on the Moodle platform which was hosted at <http://csclams.net/moodle>. The Add activity or resources block as shown in Figure 3.4a was expanded to accommodate the Pedagogy Integration Module. The menus in the module include the menu for the Author, Designer and Tutor. The Author menu has link to the interfaces for Pedagogy and Pedagogy Description Steps. The two interfaces are shown in Figure 3.4b.

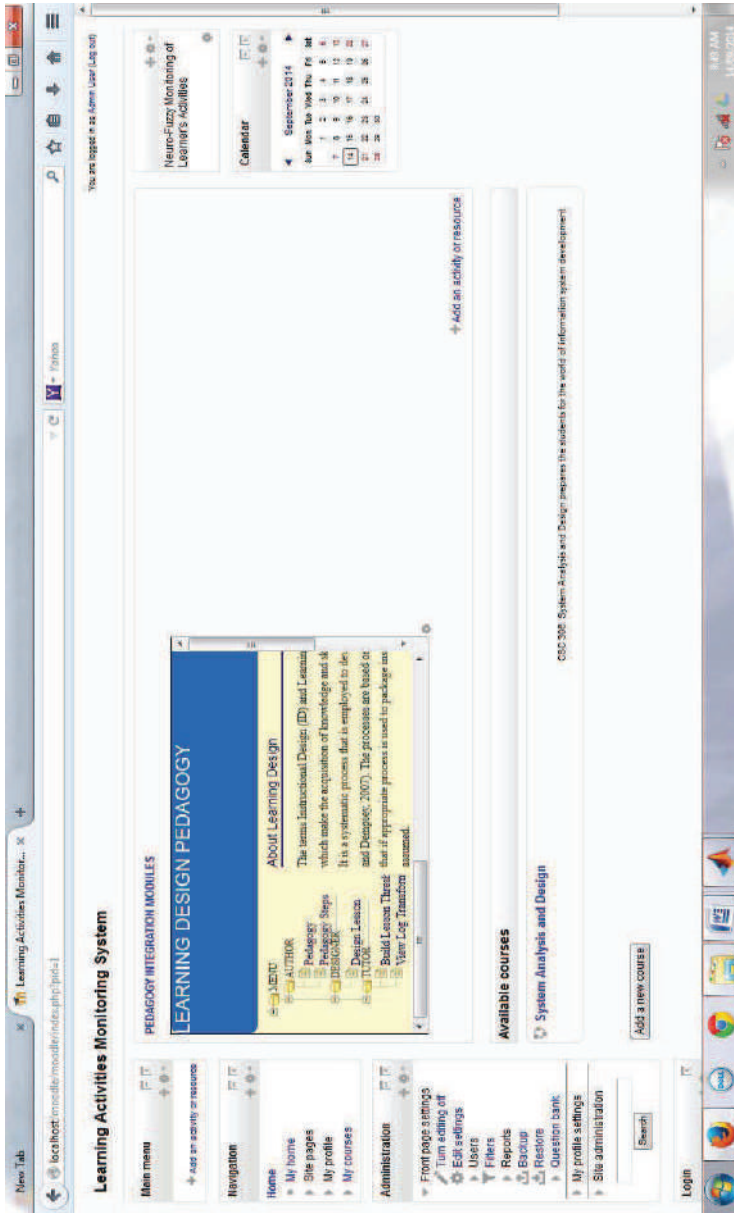


Figure 3.4a: Pedagogy Modules Integration in Moodle LMS



Figure 3.4b: Pedagogy and Pedagogy Descriptions Interfaces

The Pedagogy interface is used for supplying or modifying basic information about existing instructional design models (ID-Model). Every unique ID-model must be given an identification tag and the number of steps involved in the process must be supplied. The number of steps will auto control the description process.

The Pedagogy description interfaces are meant for data entry and editing for design tips to be displayed as guide for the teachers during the lesson construction process. The number of steps and their descriptions depends on the choice of instructional design model. If ADDIES Model is selected for instance, the steps are five (5), on the other hand, if Dick and Carey or Gagnes models are selected nine (9) steps will be iterated.

Furthermore, the Build Lesson Threshold in the Tutors menu will activate the Lesson Resources Threshold Setting Interface. This interface as shown in Figure 3.5a links lesson designers to either viewing previous collections or save newly constructed lesson thresholds. The 'View Log Transformation' link displays the aggregated students' activities as shown in Figure 3.5b for individual student. The option of viewing the activities of the whole class is available for the teacher

MENU

AUTHOR

DESIGNER

TUTOR

Lesson Resources Threshold Setting

Lesson_ID

2

Lesson Period

1

Event Step Number

Dick & Carey_4

Next Step

Pedagogy Step's Event (Responses and Actions)

Write performance objectives

Resource_ID

Resource_Category

--

Threshold

Save threshold

View Details

View Summary

Detail Lesson Information

Lesson Title:	System Analysis and Design	Total Lesson Period:	12
Pedagogy ID:	Dick & Carey	Pedagogy Name:	Dick & Carey Model
		Ped_Max_Step:	9

Detail Lesson Thresholds

S/No	Lesson ID	Period	Events	Resource ID	Resource Category	Threshold	Action
1	2	1	Download and Submission	DLoad1 & Assgn1	completion	2	DELETE
2	2	1	Download Course Outline and Submit three expected skills	DLoad1 & Assgn1	submission	1	DELETE
3	2	1	Expected Time	Time1	time	15	DELETE

Lesson Thresholds Summary

Lesson ID	Completions	Timing	Submissions	Scores	Action
2	2	15	1	0	Save

Figure 3.5a: Lesson Construction and Threshold Settings Interface

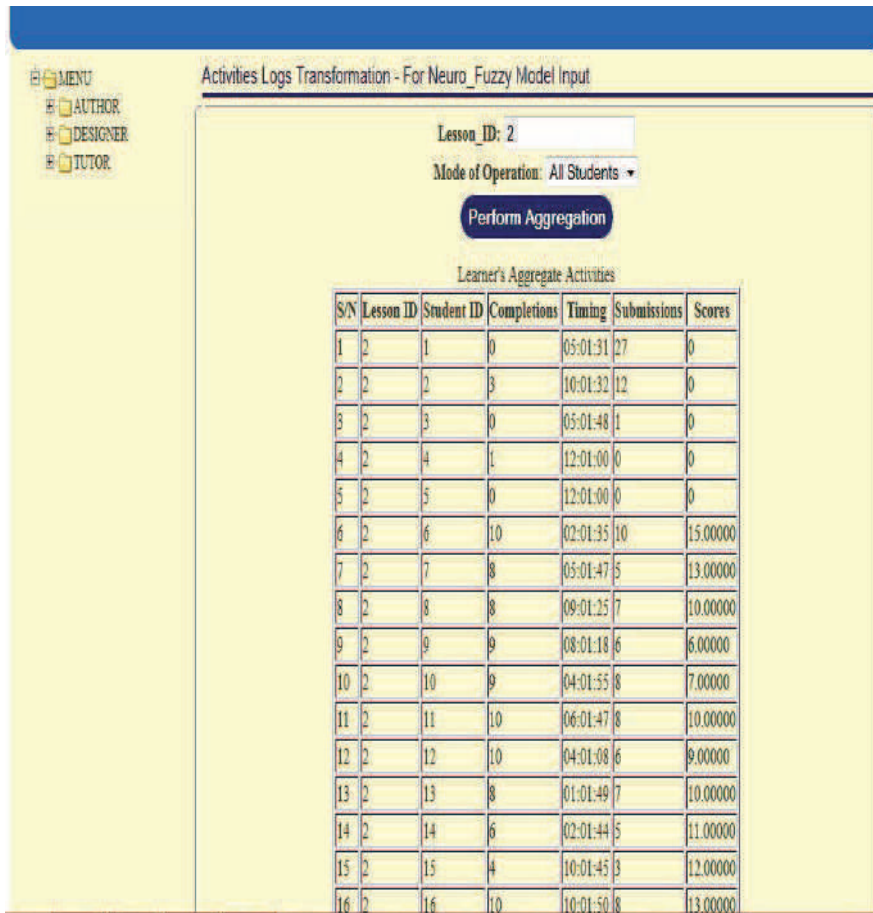


Figure 3.5b: Sample of Aggregated Log-Activities Transformations

On clicking the 'Build Lesson Threshold' link the interface will be displayed. The teacher needs to specify the lessonid. The system will auto populate the period and steps textboxes with the appropriate number from the database in accordance with course definitions. The value for the new period would be the last week / last topic plus one. Simialrly, the new steps is the next process number after the last. The system will display the next process name and its descriptions to the teacher as a guide for quality instruction design. The teacher will be required to respond by typing appropriate events, specify resources or activities for the current step.

Furthermore, the teacher would need to set the threshold for the resources and/or activities by categorising as either completion, time, submission or score. Finally the threshold integer value must be specified. Teacher needs to set the completion criteria for a given resource activity. For instance, among others, viewing every page in a document might be a criterium for its completion. The minimum number of minutes can be specified as threshold for resources/ activities categorised as 'min_time'. Here, the teacher may specify minimum time expected of a student to read a text file, listen to an audio file or watch a video clips . Integer values must be supplied as the threshold for submission and score categories. The submission threshold specifies the minimum expected number of submissions for activities like Forum, Assignment and Wiki. The score is the minimum correct answers in a quiz.

Progressively as the teacher complete the items for each step and click save button, the thresholds are auto-collated for each category to produce the aggregated values. The overall threshold for a particular lesson is an instance in the tbthreshold table with a thresholdid, datetime for the real time and date created, t_complete for the total number of completion students must have.

Others are t_time for the amount of time a student must spend in the lesson, t_submit for number of submissions and t_quiz for the expected scores a student must have in all quizzes activities.

Continuously as the lesson plan for each period are completed, the detail lesson plan can be viewed, printed or contributed to lesson repository. Furthermore, the detail lesson plan for the first period is shown in Table 3.1. The broad breakdown of CSC 306 for the semester is as shown in Table 4.5.

Table 3.1 is the excerpt from the fourteen (14) weeks learning design for CSC 306. The design was based on Dick and Carey model. It shows the course title, the semester and session for which the lesson was designed. It also specifies all the nine process, their descriptions and the teachers week 1 responses for each of the steps entered through the ‘Step Events’ textbox see Figure 3.4. The learning design is the output of the sequential learning design process for the first period.

Table 3.1: Dick and Carey based Learning Design for CSC 306

Course Title:	CSC 306: System Analysis and Design	
Semester/Session:	Rain Semester, 2013/2014 Session	
Learning Design Model:	Dick & Carey Model	
Lesson Type:	Expository	
Process	Descriptions	Week 1 Step Events
Identify Instructional Goal(s)	What is it that the learners should be able to do at completion of the instruction. The instructional goals may be defined as a list of goals, a performance analysis or a needs assessment.	Learner needs to digest the course outline and the goal of the course. They should be able to write out three skills they intended to acquire at the end of course.
Conduct Instructional Analysis	Determine the tasks, events, assets and skills that would be required for the instructions.	The student would need to enrol for the course, downloading course materials and submit forum post.
Analyze Learners and Context	Ascertain learner's goal/purpose, intellectual skills, abilities and traits of personality. Analyse the context of skills acquisition and application	All the students are 'digital native'. They are familiar with the concept of system.
Write Performance Objectives	Write the statement of what learner will be able to do, specify the	Learners would be required to register in the

	condition and the criteria for measuring performance	LMS and participate in all learning activities.
Develop Assessment Instruments	Develop assessments that are parallel to and measure the learners' ability specified in the object. It could be in any of the following test and measurement instruments: Criterion Reference Tests, Behavioural Tests, Pre- Tests, Post- Tests and Practice Tests.	Learners participating index will be estimated.
Develop Instructional Strategy	Describe the step-by-step activities towards accomplishment of the Instructional goals. The components of instructional strategies include Pre-instructional activities, Content Presentation, Learner Participation, Assessment and follow-up activities	Create and upload the course outline. Instruct students for their comments on the outline and the objective of the course. Instruct students to locate relevant course materials.
Develop and Select Instructional Materials	Specify all required artefacts, instructions, manuals, tests, modules, resources and activities.	Present recommended course materials and links
Design and Conduct Formative Evaluation of Instruction	Perform assessment of the instruction either as one-to-one, small group or field evaluation for improving the quality of design.	Teacher review students postings accordingly
Revise Instruction	Review all actions and consequents	Use survey to articulate

		students mpressions
Design and Conduct Summative Evaluations	This is not part of the design process it is however used for validating the whole process.	

3.1.4 The Learning Activities Delivery and Monitoring Architecture

The architecture for the learning activities delivery and monitoring is as shown in Figure 3.6. It is the learners-end component of the architecture. It illustrates the two (2) stores, five (5) processes and ten (10) information flows that constitute the architecture. This component has handshakes with the LDPA and the Neuro_Fuzzy Model via the Application Programme Interface (API).

The learning activities delivery and monitoring architecture illustrate the lesson repository store as a placeholder for designed lessons. The packaged learning design (a unit of learning or a lesson) is delivered to the learner as sequenced learning activities through a multimedia delivery platform. The two sided arrow multimedia information flow in the diagram emphasis the two ways information flow to and from the learner. This is one of the major modifications to the IEEE LTSA where content was indicated to flow only from the system to the learner.

Furthermore, the learner's behaviour is being tracked by the Diagnostic Evaluation Process. At this point, the learner's performance is compared with the tutors' specified thresholds during lesson construction. If the learner's participation index is satisfactory as a measure of qualitative and quantitative exploration, then the system will classify the learner as 'ready' and grant privilege for summative evaluation to the learner, otherwise the learner will be redirected to repeat the unsatisfactory activities in the lesson. All along the initiated learners profile at the point of registration will continuously be updated through learner's activities log.

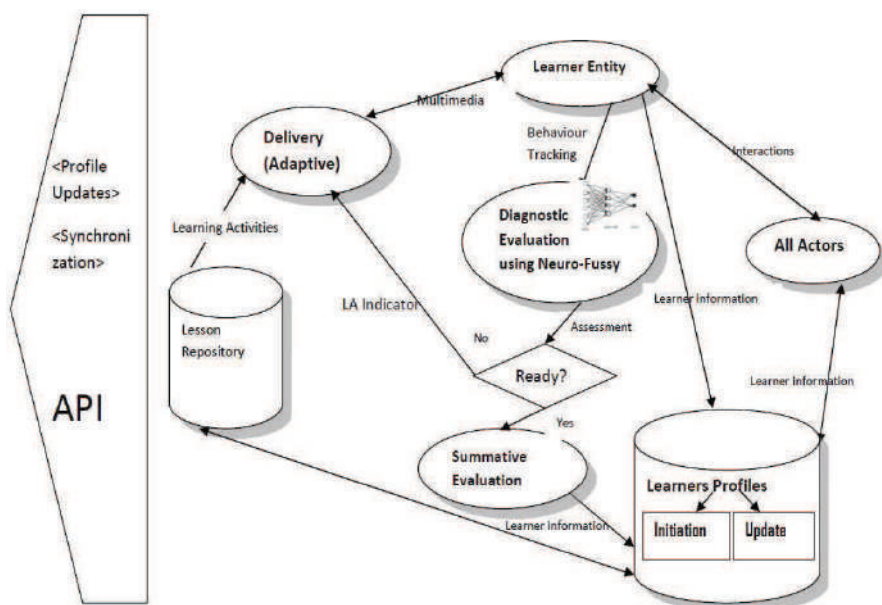


Figure 3.6: The Learning Activities Delivery and Monitoring Architecture

The 'learner - All Actors' interactions is specifically included in the model as a process for making other services providers in conventional schools play their roles also in e-learning systems. Thus, other relevant actors like, the administrative staff, school counselor, librarian, technologist and others can monitor learners profile and initiate interaction with the learner. Such actions will ameliorate some challenges of online education such as feeling of isolation, anonymity and high rate of dropouts.

3.2 Development of a Neuro-Fuzzy Learner's Activities Evaluation Model

The detail process required for the development of the neuro-fuzzy learner's activities monitoring model as a diagnostic evaluation process is abstracted in a four layers Actuator-Indicator Models as shown in Figure 3.7. The four layers are the sensor, semantic, control and indicator layers. The first two layers constitute the Monitoring/Assessment section of the actuator while the last two forms the Response section. The responsibility of the sensor layer is to aggregate and store all user information and behaviour into the Activity – log tables in the default formats. Little efforts are required to implement this layer. This is because most LMS already have inbuilt mechanism for handling the functions required of the sensor layer. The semantic layer however transforms the complex log file dataset to a predefined structured equivalent dataset. This process requires specification of the transformation rules by the teacher to serve as heuristics for generating dataset that meets the intended goal. The control and the indicator layers of the response section are implemented using the synergy of the training capability of Neural Networks and knowledge based capability of Fuzzy Logic.

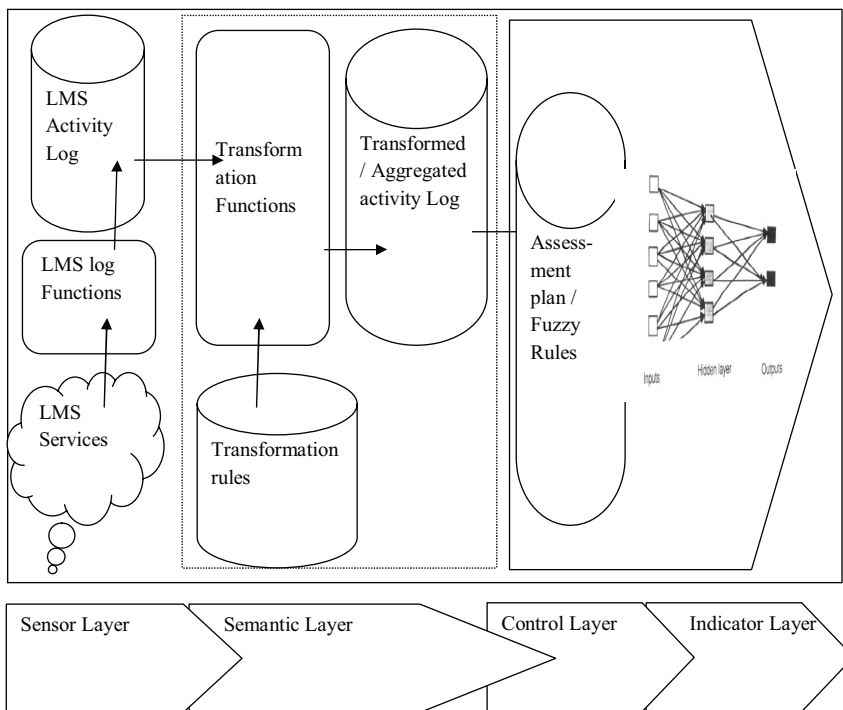


Figure 3.7: LMS Activities Tracking Architecture (Actuator Indicator Model)

Realization of the Sensor layer in Figure 3.7 was done by adopting the inbuilt mechanisms of LMS for tracking and recording of user actions and traces. Moodle which is the chosen LMS for this study stores users' traces in its database. Log tables are available for most of the activities in Moodle. The moodle tables (mdl) considered in this study include; mdl_user, mdl_log, mdl_course, mdl_course_module_completion, mdl_assignment_ submissions, mdl_forum, mdl_forum_posts, mdl_message, mdl_message, mdl_message_reads, mdl_data_content, mdl_data_records, mdl_feedback, mdl_feedback_tracking, mdl_quiz, mdl_quiz_attempts and mdl_quiz_grades. Appendix B collates most of the mdl_ tables in a typical moodle installation. The sensor layer therefore logs data of users' actions through the corresponding log functions into the log tables. The fields in the tables vary according to the nature of operations in the moodle activities or resources it represents. The content and context are usually in large, bewildered and complex form which necessitates transformation, harmonization and interpretation for efficient use.

Actualization of the Semantic layer necessitates creation of transformation functions for each type of resources being considered. The functions transformed contents of activities log files usually in general format to a predefined format stored in Aggregated Activity Log table created as 'transformedtb'. The transformation functions invokes appropriate mathematical or statistical operators in a predefined formats towards estimations of the four categories of inputs (*time spent reading, content completion status, participation index and diagnosis assessment*). A typical instance and resultant product of this layer is as shown in Table3.2.

Table 3.2. Transformed Aggregated Activity Log Schema

mdl-tables	Attributes	Transformation	Aggregate Attributes	Descriptions
~~(mdl_course)~~	id; username; password; firstname; lastname; email; phone1; phone2; address; timemodified	Select * from mdl_users where id=user_id		Information of registered students in a course
mdl_log	id; time; userid; ip; course; module; cmid; action; url; info	- Select (action using userid)-Aggregate (action using cmid and userid)	course_id	Logged every users actions
mdl_course_completion	id; userid; course; timeenrolled; timestarted; timecompleted; reaggregation	Count (timecompleted using id, userid and course)	n_course	Total number of completed course
mdl_course_completion	Ditto	Subtract (timestarted, timecompleted)	t_course	Total time spent in the course

mdl_assignm ent _submissions	Id; assignment; userid; timecreated; timemodified; numfiles;data1; data2; grade; submissioncomment; format; teacher; timemarked; mailed	Count (numfiles using id, assignment and userid)	n_assignment	Number of assignment submitted
mdl_assignm ent _submissions	Ditto	Subtract (timecreated, mdl_assignment(timeava ilable))	t_assignment	Determine the response time
mdl_forum _posts	Id; discussion; parent; userid; created; modified; mailed; subject; message; format; attachment; totalscore	Count(message using id and userid)	n_forum_post	Number of forum post
mdl_forum _read	Id; userid; forumid; discussionid; postid; firstread; lastread	Count(firstread using id, usrld and forumid)	t_msg_read	Total number of message

mdl_quiz_attempts	Id; quiz; userid;attempt; uniqueid; laout; currentpage; preview; state; timestart; timefinish; timemodified; timecheckstate; sumgrades; needsupgradetonewqe	Count(attempt using id, quiz and userid)	t_quiz_attam pt	Total attempt quiz
mdl_quiz_grades	Id; quiz; userid; grade; timemodified	Average (grade => 40 using id, quiz and userid)	p_quiz	Total passed quiz

The Control layer adopts the thresholds specified during lesson construction for benchmarking the performance of every student enrolled in the lesson. The threshold stored in the 'thresholdtb' created in section 3.1.3.1 is the teacher's evaluation strategy and action plans needed to be transferred to the system. In addition, the fuzzy rule on which the network would be trained needs also be specified. Expectedly, for each of the attributes to be included in the model, the teacher needs to specify the attribute ratings, the grading style and the consequences (actions) for all the possible combinations. The benchmarking values may be in discrete figure or in percentages. The discretized value will also need to be fuzzified by the teacher as input into the Indicator Layer. Sections 3.2.1 to 3.2.5 detail the techniques used to actualize the control layer and the indicator layer. However, where training dataset is available, such could be used directly by the system for rule generation, membership function specification and pattern recognition. This capability of dual approach to system construction and parameters adjustment underscore the choice of Neuro-Fuzzy Model.

The Indicator Layer is the last layer in the Actuator Indicator Model which is the place holder for the Neuro-Fuzzy Model. The Neuro-Fuzzy technique is a diversion from the visualization approaches conventionally used for learners activities indicators. The input for this layer is harvested from the output of the control layer. The detail design process for this layer is subsequently described in section 3.2.1 to section 3.2.5.

3.2.1 Modelling of Learner's Activities Exploration and Concentration

In soft-computing paradigms, system modelling is based on structure identification and parameter identification. The source of structural information could be experts or a prior data. The extent to which each of these sources is used

qualifies a model as either white box, black box or grey box. These three types of models are accomplishable using Fuzzy Logic, Neural Network and Neuro-Fuzzy models respectively. The choice of Fuzzy based Neural Network (Neuro-Fuzzy) model was made in this study after it was experimentally determined to be best for the learner's e-learning activities evaluation.

Furthermore, the three standard models in adaptive system are the domain model, the user model and the adaptive model. The focus of this study however is the user (student) model which is the heart of any adaptive system. The two main features being modelled (Exploration and Concentration) are 'low bandwidth' features. They are so attributed because information about them is not readily evident. The duo can only be deduced from other readily available information. To this end relevant LMS activities and resources were aggregated, transformed and adopted as input for the inference system.

To actualize this in this research, CSC 306 (System Analysis and Design) lessons was packaged using pedagogical grounded approach as described in section 3.1.2. For the purpose of modeling, the term "Exploration" was coined for quantitative measurement, while the term "Concentration" is for qualitative interactions. Quantitative exploration is a function of percentage (%) course completion and amount of time spent on the course. The qualitative measurement is a function of participation level (index). It would be deduced logically from the information available from all activities that require submissions. Such activities include assignment submission, forum post and messages initiated, read or replied. The other component used for the qualitative measurement is quiz grade used as diagnostic assessment. The overall intention is to automatically calculate students participation index for the purpose of classifying them as either ready to proceed for summative evaluation or to repeat a lesson.

The modeling algorithm is as follows:

- i. Defining the Input / Output values
- ii. Defining fuzzy sets for Input and Output values
- iii. Defining fuzzy rules
- iv. Creating and training the Neuro-Fuzzy Network

3.2.2 Defining the Input / Output Values

Students modelling require identifying the **N** group of observable behaviours to be used as input for the model. This specification is necessary to provide a scope for the model, since there are many sides to student issues and several attributes can be used by a teacher to describe a learner. Hence, for every N_i , there could be **B** stimuli or linguistic variables and for every B_i there could be **F** linguistic values or linguistic terms. Every F_i is a fuzzification of $x_i \in U_i$, while $U_i \subset R^+$ and R^+ symbolizes the base values.

Having identified the **N** group of observable behaviours, the names and values for both **B** and the **F** are normally determined in consultation with the experts. Such that the term set $T(B_i) = \{V_{i1}, V_{i2}, V_{ifi}\}$ is the set of all values for B_i and the set $T = \{T(B_1), T(B_2), \dots, T(B_n)\}$ represent the set of overall observable behaviours **B** to be considered in the model. Furthermore, the numerical input $X = \{x_1, x_2, \dots, x_n\}$ that represents the values of $B = \{B_1, B_2, \dots, B_n\}$ is fuzzified by means of linguistic values $\{V_{11}, V_{12}, \dots, V_{1fi}; V_{21}, V_{22}, \dots, V_{2fi}; \dots V_{n1}, V_{n2}, \dots, V_{nfn}\}$ as considered appropriate. The implication of this representation is that the set of student behaviour **B** is represented as a set of numeric values $Y = \{(y_{11}, y_{12}, \dots, y_{1f1}), (y_{21}, y_{22}, \dots, y_{2f2}), \dots (y_{n1}, y_{n2}, \dots, y_{nfn})\}$ in the close range $[0,1]$. Each representation denotes the degree of membership of each numeric value x_i into the set of B_i with linguistic values $V_{11}, V_{12}, \dots, V_{1fi}$.

Specifically, the student model in this research considered two groups of observable behaviours for diagnosis, hence, the N is equals to two (2). The two groups are content exploration (N_1) and extent of concentration (N_2). For N_1 the two linguistic variables (B_1, B_2) are considered as total time spent on the course and content completion status. For N_2 two linguistic variables (B_3, B_4) are also considered as the participation index and diagnosis assessment remarks.

The N_1 (Exploration) has $\{B_1, B_2\} = \{\text{total time spent reading, content completion status}\}$. The linguistic values for describing B_1 are $\{\text{low, medium, high}\}$. Hence, for B_1 (*total time spent reading*) the $B_1f_1 = 3$. These values are the tutor's opinion of the cumulative time spent by the learner on the courseware when compared with the experts expected time estimates as contained in the threshold. For B_2 (*content completion status*) the $B_2f_2 = 2$. The linguistic values for describing B_2 are $\{\text{Non-adequate, Adequate}\}$. The fuzzy set reflects the amount of students' exploration against the completion thresholds specified by the tutor.

Similarly, the N_2 (Concentration) has $\{B_3, B_4\} = \{\text{the participation index, diagnosis assessment remarks}\}$. The linguistic values for the B_3 (*the participation index*) = (high, medium, low). Finally, the linguistic values for the B_4 (*diagnosis assessment remarks*) = (Unsatisfactory, Satisfactory), so the $B_3f_3 = 3$ while the $B_4f_4 = 2$. Summarily, the input can be described as follows:

$N = 2 = \{N_1, N_2\} = \{\text{Exploration, Concentration}\}$

N_1 (Exploration) = $\{B_1, B_2\} = \{\text{total time spent reading, content completion status}\}$

N_2 (Concentration) = $\{B_3, B_4\} = \{\text{the participation index, diagnosis assessment remarks}\}$

Model Term set $T = \{T(B_1), T(B_2), T(B_3), T(B_4)\}$

$T(B_1) = \{\text{total time spent reading}\} = \{L, M, H\} = B_1f_1 = 3$ linguistic variables

$T(B_2) = \{\text{content completion status}\} = \{NA, A\} = B_2f_2 = 2$ linguistic variables

$T(B_3) = \{\text{the participation index}\} = \{L, M, H\} = B_3f_3 = 3$ linguistic variables

$T(B_4) = \{\text{diagnosis assessment remarks}\} = \{U, S\} = B_4f_4 = 2$ linguistic variables

Hence, the model's term set $T(N) = \{(L, M, H), (NA, A), (L, M, H), (U, S)\}$. Figure 3.8 is a Decision Tree that depicts all possible combinations. In it L stands for Low, M for Medium, and H for High. Furthermore, NA is for Non-Adequate, A for Adequate, U for Unsatisfactory, and S for Satisfactory.

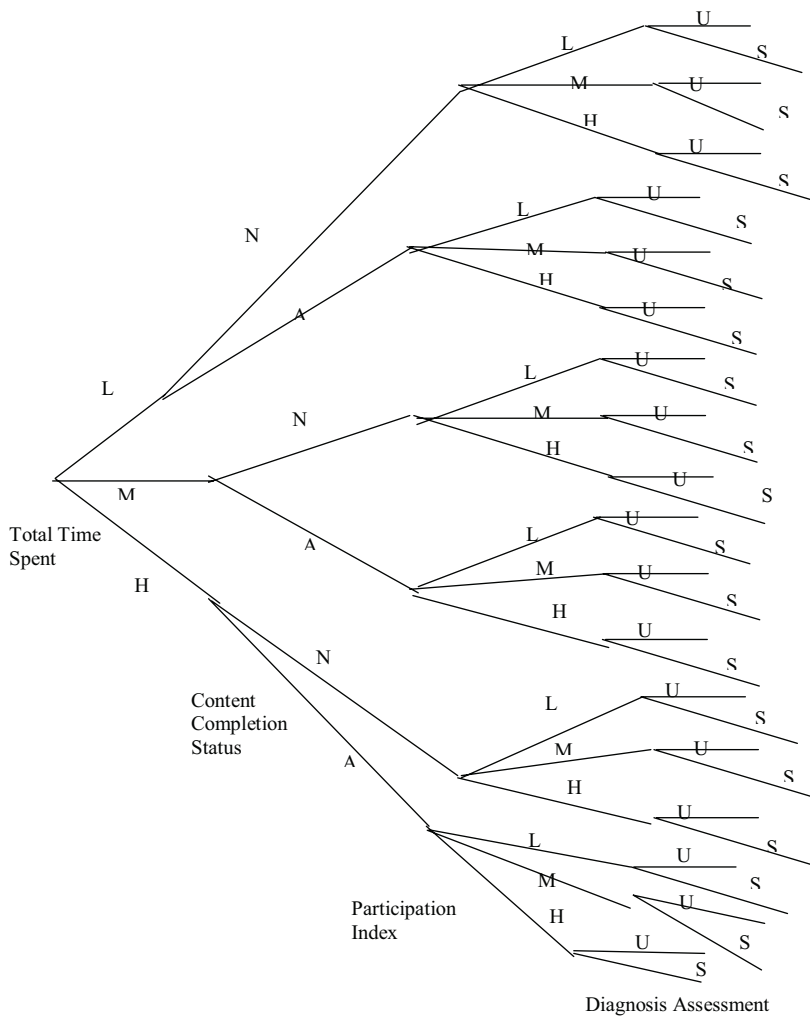


Figure 3.8: Decision Tree for Students Content Exploration and Concentration

Concurrently as the inputs were identified, the required outputs were also specified. The output reflects the essence of the model. It is usually the product of the expert's decision in classifying the students into one of the predefined set of characters C expressed in linguistic variable on the bases of the observable behaviours. Each of the character C_j can take m_j number of distinct value. The term set of C_j , $T(C_j) = \{C_{j1}, C_{j2}, \dots, C_{jm_j}\}$. The expert was consulted to determine the number and values of C_j and m_j . It is common to employ defuzzification functions to facilitate adequate representation of expert's subjective decisions. The decision or output may be marginal (as in very low, low, high and very high) or clear-cut as in pass or fail. However, the purpose of this model is to classify learner to either 'Repeat a course' or 'Proceed to Examination' for final achievement test, hence the C is equals to 2.

$$T(C) = \{\text{Repeat, Proceed}\} \approx \{0 \leq T(C) \leq 45, 45 < T(C) \leq 100\}.$$

3.2.3 Defining Fuzzy Sets for the Input and Output Values

Linguistic variables in fuzzy system are functions of the base values. The base values could be discrete or continuous values. In fuzzy logic terminology, the mathematical functions that perform the transformation are known as membership functions. The membership functions (MF) are curves that approximate the base value to a continuous degree of membership in close range $[0 \ 1]$. The Gaussian MF was chosen in this work because its parameter (c – *centre* and σ – *width*) are amenable to adjustment through training. The membership function graph for the output is shown in Figure 3.9 (e). The descriptions of the transformation approach used for the four input linguistic variables considered for determining students' exploration and concentration in this study are as follows.

Exploration: Determining students' progress on the basis of course material coverage is obviously possible. This is because the completion criteria for all course activities and resources can be set. Any student that meets the specified conditions would have the activities or resources status marked as 'complete' automatically and store in the mdl_course_completion table. The number of completed resources over the threshold values will be estimated. Similarly, the time spent by the students on the course is considered as a measure of commitments. The transformation approaches for content completion and time spent are as follows:

- i. Total Time Spent Reading which can either be Low, Medium or High is expressed as

$$x_t = \frac{\sum te}{T} \times 100 \quad (3.1)$$

where te is the time spent by the learner on the lesson. The teacher would have specified the expected time for each activities and resources that constitute the lesson. T is the total threshold for the time in seconds. From Section 3.4.1, $T(B_1) = \{\text{total time spent reading}\} = \{L, M, H\} = B_1 f_1 = 3$ linguistic variables = { Low, Medium, High} $\approx \{0 \leq T(B_1) \leq 30, 30 < T(B_1) < 70, 70 \leq T(B_1) \leq 100\}$. Figure 3.9 (a) shows the membership graph.

- ii. Content Completion Status can either be Non-Adequate or Adequate. It is expressed as

$$x_c = \frac{\sum Ce}{C} \times 100 \quad (3.2)$$

where Ce is the number of modules, resources or activities completed by the learner. C is the threshold set by the teacher for total number of completions required. From Section 3.4.1, $T(B_2) = \{\text{content completion status}\} = \{\text{Non Adequate, Adequate}\} \approx \{0 \leq T(B_2) \leq 45, 45 < T(B_2) \leq 100\}$. Figure 3.9 (b) shows the membership graph.

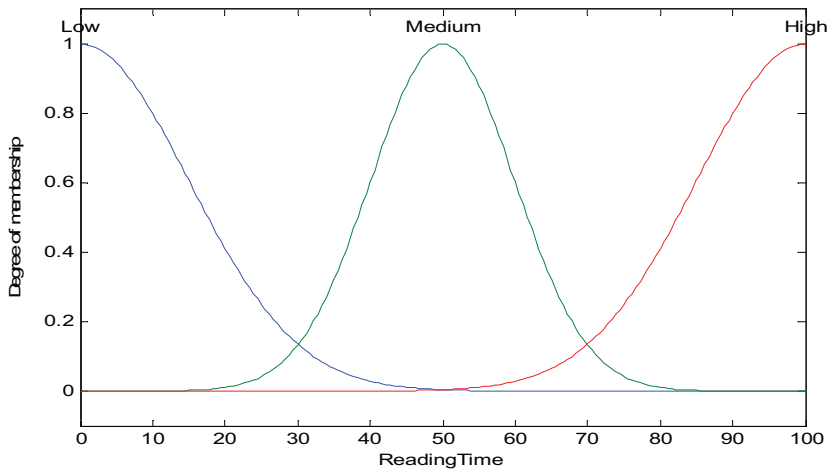


Figure 3.9 (a): Reading Time Membership Function

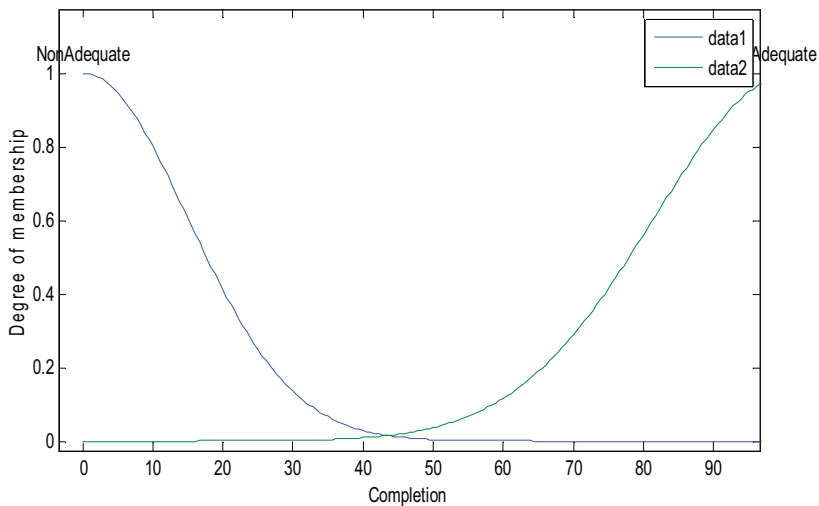


Figure 3.9 (b): Completion Membership Function

Concentration: Determining students' level of concentration or degree of seriousness in E-learning system is more challenging than that of content exploration. It is a feature that can only be deduced from other activities. The approach used in this research is to determine it from students' level of participation in class activities. Such information can be harvested from mdl_assignment_submission, mdl_forum_post, mdl_forum_read, mdl_message among others. Table 3.1 has the details of the applicable attributes in the identified tables.

iii. Participation Index of any learner can either be Low, Medium or High. It is expressed as

$$x_p = \frac{\sum pe}{P} \times 100 \quad (3.3)$$

where $\sum pe$ is the summation of all participation values estimate for the student x , while P is the participation index threshold set by the teacher.

From 3.4.1 $T(B_3) = \{\text{the participation index}\} = \{L, M, H\} = B_3f_3 = 3$ linguistic variables = { Low, Medium, High} $\approx \{0 \leq T(B_3) \leq 30, 30 < T(B_3) < 70, 70 \leq T(B_3) \leq 100\}$. Figure 3.9 (c) shows the membership graph.

iv. Diagnosis Assessment Remarks can either be Unsatisfactory or Satisfactory. It

is also expressed as
$$x_d = \frac{\sum q}{Q} \times 100 \quad (3.4)$$

where q is the number of correct diagnostic questions, Q is the number of diagnostic questions available.

$T(B_4) = \{\text{diagnosis assessment remarks}\} = \{U, S\} = B_4f_4 = 2$ linguistic variables = {Unsatisfaction, Satisfaction} $\approx \{0 \leq T(B_4) \leq 45, 45 < T(B_4) \leq 100\}$. Figure 3.9 (d) shows the membership graph.

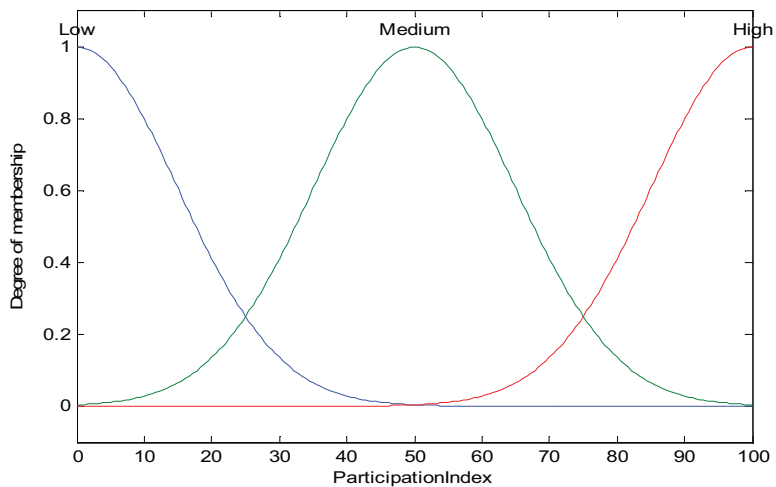


Figure 3.9 (c): Participation Index Membership Function

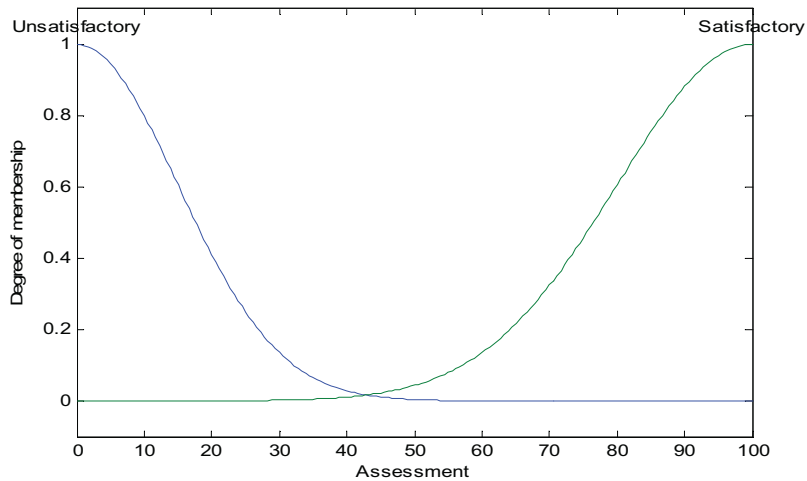


Figure 3.9 (d): Diagnostic Assessment Membership Function

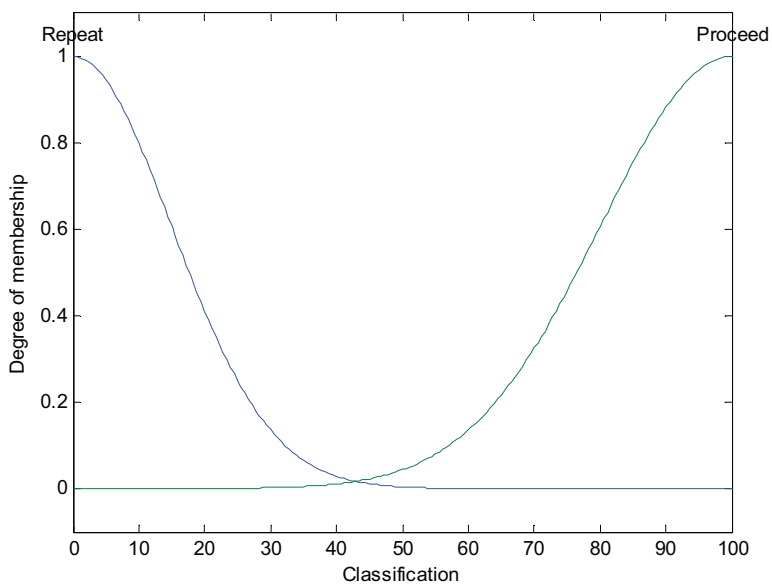


Figure 3.9(e) Classification Membership Function.

3.2.4 Defining Fuzzy Rules

In between the input stage and the output stage is the inference stage. This is where the experts reasoning are approximately represented in a series of IF-THEN rules. The premises and conclusions are fuzzily expressed. It is a possible, subjective and non probable values; it depends on the feeling of the tutor on each of the metrics. Using Generalised Modus Ponens, tautology in the premise and consequent have discrete values, a typical rule can be expressed as:

IF (*Time spent reading is low*) AND (*Content completion status is Non-Adequate*) AND (*Participation index is low*) AND (*Diagnostic assessment is Unsatisfactory*) THEN *Learner Repeat Course*.

Generally,

"IF B_1 is V_{1i_1} AND B_2 is V_{2i_2} AND ... B_n is V_{ni_n} THEN C_1 is C_{1j_1} AND C_2 is C_{2j_2} ... AND C_n is C_{nj_n} "

Where $i_1 = 1, 2, \dots, f1$; $i_2 = 1, 2, \dots, f2$; $i_n = 1, 2, \dots, fn$; $j_1 = 1, 2, \dots, m1$; $j_2 = 1, 2, \dots, m2$; $j_m = 1, 2, \dots, mm$.

The combination of all the individual observable behaviours resulted into the Cartesian product of the set in $T = \{T(B_1), T(B_2), \dots, T(B_n)\} = T(B_1) \times T(B_2) \times \dots \times T(B_n)$ this resulted in n possible cases in the overall premises to the final conclusion. That is $n = f1 \times f2 \times \dots \times fn$.

Putting it succinctly as in Stathacopoulou *et al.* (2004) the student model can be expressed as

$$P^o R_j = C_j \quad (3.5)$$

where vector $P = [p_1, p_2, \dots, p_n]^T$ - denotes the students' behaviours being modelled.

R_j is a $n \times m_j$ weight matrix representing teacher / expert's estimations of the degree of association between observable behaviour P and the linguistic values of the student's characteristics C_j . C_j is an m -dimensional vector $C_j = [c_{j1}, c_{j2}, \dots, c_{jm_j}]^T$ with c_{j1}, c_{j2}, c_{jm_j} in $[0,1]$ representing the fuzzy assessment of the students character C_j i.e. an assessment with membership degrees $c_{j1}, c_{j2}, \dots, c_{jm_j}$ on each linguistic value $(C_{j1}, C_{j2}, \dots, C_{jm_j})$ of the linguistic variable for the characteristic C_j . The symbol $\circ$ denotes the max-min composition operator.

The Decision Tree used to visualize and classify the rules as shown in Figure 3.8 is the basis for generating the Rule Table shown in Table 3.3. The $3 \times 2 \times 3 \times 2$ premises will produce thirty six (36) consequents. A typical experts' decision on the thirty six possible premises is shown in table. Few justifications for the expert's decision were provided while others were not supplied. This is purposely done to illustrate that the justification for the decision is debatable and discretionary. Furthermore, a teacher may not set or use all of the thirty six rules.

Table 3.3: The Rule Table

<i>Rule Number</i>	<i>PREMISE (Using AND Operator)</i>					<i>CONSEQUENT</i>	<i>JUSTIFICATIONS</i>
	<i>Time spent reading</i>	<i>Content completion status</i>	<i>Participation index</i>	<i>Diagnosis assessment</i>	<i>Experts decision</i>		
<i>1</i>	<i>L</i>	<i>N</i>	<i>L</i>	<i>U</i>	<i>R</i>		<i>Content must be completed</i>
<i>2</i>	<i>L</i>	<i>N</i>	<i>L</i>	<i>S</i>	<i>R</i>		<i>Content must be completed</i>
<i>3</i>	<i>L</i>	<i>N</i>	<i>M</i>	<i>U</i>	<i>R</i>		<i>Content must be completed</i>
<i>4</i>	<i>L</i>	<i>N</i>	<i>M</i>	<i>S</i>	<i>R</i>		<i>Content must be completed</i>
<i>5</i>	<i>L</i>	<i>N</i>	<i>H</i>	<i>U</i>	<i>R</i>		<i>Content must be completed</i>
<i>6</i>	<i>L</i>	<i>N</i>	<i>H</i>	<i>S</i>	<i>R</i>		<i>Content must be completed</i>
<i>7</i>	<i>L</i>	<i>A</i>	<i>L</i>	<i>U</i>	<i>R</i>		<i>Just scrolling the materials</i>
<i>8</i>	<i>L</i>	<i>A</i>	<i>L</i>	<i>S</i>	<i>P</i>		<i>Content is well covered and understood</i>

9	<i>L</i>	<i>A</i>	<i>M</i>	<i>U</i>	<i>R</i>	
10	<i>L</i>	<i>A</i>	<i>M</i>	<i>S</i>	<i>P</i>	
11	<i>L</i>	<i>A</i>	<i>H</i>	<i>U</i>	<i>P</i>	
12	<i>L</i>	<i>A</i>	<i>H</i>	<i>S</i>	<i>P</i>	
13	<i>M</i>	<i>N</i>	<i>L</i>	<i>U</i>	<i>R</i>	
14	<i>M</i>	<i>N</i>	<i>L</i>	<i>S</i>	<i>R</i>	
15	<i>M</i>	<i>N</i>	<i>M</i>	<i>U</i>	<i>R</i>	
16	<i>M</i>	<i>N</i>	<i>M</i>	<i>S</i>	<i>R</i>	
17	<i>M</i>	<i>N</i>	<i>H</i>	<i>U</i>	<i>R</i>	
18	<i>M</i>	<i>N</i>	<i>H</i>	<i>S</i>	<i>R</i>	
19	<i>M</i>	<i>A</i>	<i>L</i>	<i>U</i>	<i>R</i>	
20	<i>M</i>	<i>A</i>	<i>L</i>	<i>S</i>	<i>P</i>	
21	<i>M</i>	<i>A</i>	<i>M</i>	<i>U</i>	<i>R</i>	
22	<i>M</i>	<i>A</i>	<i>M</i>	<i>S</i>	<i>P</i>	
23	<i>M</i>	<i>A</i>	<i>H</i>	<i>U</i>	<i>P</i>	
24	<i>M</i>	<i>A</i>	<i>H</i>	<i>S</i>	<i>P</i>	
25	<i>H</i>	<i>N</i>	<i>L</i>	<i>U</i>	<i>R</i>	
26	<i>H</i>	<i>N</i>	<i>L</i>	<i>S</i>	<i>R</i>	
27	<i>H</i>	<i>N</i>	<i>M</i>	<i>U</i>	<i>R</i>	
28	<i>H</i>	<i>N</i>	<i>M</i>	<i>S</i>	<i>R</i>	
29	<i>H</i>	<i>N</i>	<i>H</i>	<i>U</i>	<i>R</i>	

30	H	N	H	S	R	
31	H	A	L	U	R	
32	H	A	L	S	P	
33	H	A	M	U	P	
34	H	A	M	S	P	
35	H	A	H	U	P	
36	H	A	H	S	P	
Key: L=Low, M=Medium, H=High, N=Non Adequate, A=Adequate, U=Unsatisfactory, S=Satisfactory, P=Proceed, R=Repeat						

3.2.5 Creating and Training the Neuro-Fuzzy Network

Provisions in the previous three steps offer a good ground for White-Box and Gray-Box modelling of student's learning activity evaluations. The four stages used for the creation and training of the Neuro-Fuzzy Network are formulation of a Mamdani Fuzzy model, transformation of Mamdani Fuzzy model to its Sugeno Fuzzy model equivalent, formulation of the required Neuro – Fuzzy model and the Network training. Details of each stage of the procedure follow.

Stage 1: Formulation of Mamdani Fuzzy Model for Learner's Activities Evaluation

The intent of developing the Mamdani Fuzzy model was to provide structural specification for the intended Neuro-Fuzzy Model and to provide basis for measuring the efficacy of Neuro-Fuzzy Model (Gray-box model) over Fuzzy Model (White-box model). The algorithm for the model and the explanations for each are as follows.

- i. Fuzzification of the system input
- ii. Formulation of fuzzy rules
- iii. Building Mamdani Fuzzy Inferences

Step i. Fuzzification of the System Input

The fuzzification of input for the system is as explained in section 3.2.3

Step ii. Formulation of Fuzzy Rules

The Mamdani Model or a linguistic fuzzy model of the system with four inputs and one output is specified as series of if-then rules of the form

$$R_i = \text{if } \bar{u} \text{ is } A_i \text{ AND } \bar{v} \text{ is } B_i \text{ AND } \bar{w} \text{ is } C_i \text{ AND } \bar{x} \text{ is } D_i \text{ then } \bar{y} \text{ is } E_i \quad (3.6)$$

where $i = 1, 2, \dots, 36$. $\bar{u}, \bar{v}, \bar{w}$ and $\bar{x}$ are the linguistic variables for the antecedent; the linguistic terms for the antecedent are A_i, B_i, C_i and D_i . $\bar{y}$ is the linguistic

variables for the consequent, its linguistic terms is E_i . Furthermore, for the premise $u \in U, v \in V, w \in W, x \in X$, where $U, V, W, X \subset R^p$, while for the consequent $y \in Y \subset R^q$. The membership functions of u, v, w and x are the mappings $\mu(u): U \rightarrow [0,1]$, $\mu(v): V \rightarrow [0,1]$, $\mu(w): W \rightarrow [0,1]$, $\mu(x): X \rightarrow [0,1]$, and $\mu(y): Y \rightarrow [0,1]$ respectively. When A, B, C, D and E are the domains then the linguistic terms $A_i \in A, B_i \in B, C_i \in C, D_i \in D$ and $E_i \in E$ holds. The rule base which constitute the qualitative relationship between the model input and output is given as

$$R = \{R_i | i = 1, 2, 3, \dots, 36\} \quad (3.7)$$

The thirty six (36) rules are as summarized in section 3.2.4.

Step iii. Building Mamdani Fuzzy Inferences

For the model to be effective, its inference mechanism must be built on specific relational representation, which could either be by using fuzzy conjunction or by using fuzzy implications. The Relational representation of linguistic model used in this work is the fuzzy conjunctions. This is informed by the fact that all the variables are expected to hold. The Mamdani (conjunction) relation R is computed by the minimum ($\wedge$) operator. Fuzzy Inference Engine could be designed using either the Composition Based Inference Firing or Individual Rule Based Inference Firing.

The discretizations for the membership functions in Figure 3.9 (a-e) are presented in Table 3.4 (a-e) respectively, the values are used to compute the firing strength of Rule 1 base on equation 3.8. The discretizations were built on interval 25 in the range 0 – 100. The RT – Reading Time is the discretization for Figure 3.9a, the C – Completion is for Figure 3.9b, the P – Participation is for Figure 3.9c, the A – Assessment is for Figure 3.9d, the CL – Classification is Figure 3.9e.

Table 3.4(a): Discritization for Reading Time Variable

RT	0	25	50	75	100
Low	1.0	0.25	0.0	0.0	0.0
Medium	0.0	0.03	1.0	0.03	0.0
High	0.0	0.0	0.0	0.25	1.0

Table 3.4(b): Discritization for Completion Variable

C	0	25	50	75	100
Non-adequate	1.0	0.27	0.0	0.0	0.0
Adequate	0.0	0.0	0.03	0.35	1.0

Table 3.4(c): Discritization for Participation Variable

P	0	25	50	75	100
Low	1.0	0.25	0.0	0.0	0.0
Medium	0.0	0.03	1.0	0.03	0.0
High	0.0	0.0	0.0	0.25	1.0

Table 3.4(d): Discritization for Assessment Variable

C	0	25	50	75	100
Unsatisfactory	1.0	0.27	0.0	0.0	0.0
Satisfactory	0.0	0.03	0.0	0.35	1.0

Table 3.4(e): Discritization for Classification Variable

CL	0	25	50	75	100
Repeat	1.0	0.27	0.0	0.0	0.0
Proceed	0.0	0.0	0.03	0.35	1.0

The Composition Based Inference Firing: the firing strength ω_i for each rule

R_i is given as

$$\begin{aligned}\omega_i = R_i &= A_i \times B_i \times C_i \times D_i \times E_i = R_i(u, v, w, x, y) = \\ \mu A_i(u) \wedge \mu B_i(v) \wedge \mu C_i(w) \wedge \mu D_i(x) \wedge \mu E_i(y) &= \\ \min [\mu A_i(u), \mu B_i(v), \mu C_i(w), \mu D_i(x), \mu E_i(y)]\end{aligned}\quad (3.8)$$

The fuzzy relation R representing the entire model (Equation 3.7) is given by the disjunction (Union) of the K individual rule's relations R_i

$$\begin{aligned}R = \bigcup_{i=1}^{36} R_i &= \mu_R(u, v, w, x, y) = \\ \frac{\max_{1 \leq i \leq 36}}{1} [\mu A_i(u) \wedge \mu B_i(v) \wedge \mu C_i(w) \wedge \mu D_i(x) \wedge \mu E_i(y)]\end{aligned}\quad (3.9)$$

With the entire rule base encoded in the fuzzy relation R, the output of the linguistic model can be computed by the relational max-min composition (o).

$$\bar{y} = (\bar{u}, \bar{v}, \bar{w}, \bar{x}) o R \quad (3.10)$$

For Rule 1, $R_1 =$ If (Reading Time is Low) and (Completion is NonAdequate) and (ParticipationIndex is Low) and (Assessment is Unsatisfactory) then (Classification is Repeat) the firing strength from Equation 3.8 is the Cartesian products of the five variables as shown below:

$$\omega_1 = R_1 = TR_L \times C_N \times P_L \times A_U \times CL_R =$$

$$\begin{aligned}\mu A_i(u) \wedge \mu B_i(v) \wedge \mu C_i(w) \wedge \mu D_i(x) \wedge \mu E_i(y) &= \\ \min [\mu A_i(u), \mu B_i(v), \mu C_i(w), \mu D_i(x), \mu E_i(y)] &= \\ \min(RT_L, C_N) &\end{aligned}$$

	1.0	0.27	0.0	0.0	0.0
1.0	1.0	0.27	0.0	0.0	0.0
0.25	0.25	0.25	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0

$$\min(\text{TR}_L, \text{C}_N, \text{P}_L)$$

$$\begin{pmatrix} 1.0 & 0.27 & 0.0 & 0.0 & 0.0 \\ 0.25 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{pmatrix} \begin{pmatrix} 1.0 \\ 0.25 \\ 0.0 \\ 0.0 \\ 0.0 \end{pmatrix} \quad \begin{pmatrix} 1.0 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.25 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{pmatrix}$$

$$\min(\text{RT}_L, \text{C}_N, \text{P}_L, \text{A}_U)$$

$$\begin{pmatrix} 1.0 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.25 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{pmatrix} \begin{pmatrix} 1.0 \\ 0.27 \\ 0.0 \\ 0.0 \\ 0.0 \end{pmatrix} \quad \begin{pmatrix} 1.0 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.25 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{pmatrix}$$

$$\min(\text{RT}_L, \text{C}_N, \text{P}_L, \text{A}_U, \text{CL}_R) \quad = \quad \omega_1$$

$$\begin{pmatrix} 1.0 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.25 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{pmatrix} \begin{pmatrix} 1.0 \\ 0.27 \\ 0.0 \\ 0.0 \\ 0.0 \end{pmatrix} \quad \begin{pmatrix} 1.0 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.25 & 0.25 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{pmatrix}$$

The specified process estimates only the first firing strength for the R_1 . So using the same approach the relation for other rules is constructed. The fuzzy relation R representing the entire model is as given by the disjunction (Union) of the individual rule's relations R_i as in (3.6).

The Individual Rule Based Inference Firing or the max-min (mamdani) inference: Using the Composition Based Inference Firing or Relational Calculus approach as described require a lot of computational time and memory for storing individual relations. This is evident in the computation of the firing strength ω_1 for rule 1. Hence, to bypass the relational calculus and its challenges, the Individual Rule Based Inference Firing or the max-min (mamdani) inference was considered the most appropriate as recommended in (Babuska, 2001).

The working of the Individual Rule Based Inference Firing or the max-min (mamdani) inference is constructed by considering the input fuzzy value $\bar{K} = K'$, for which the expected output value is E' , the relational composition is given as:

$$\mu E'(y) = \frac{\max}{x} \{ \mu_{K'}(u, v, w, x) \wedge \frac{\max}{1 \leq i \leq 36} [\mu A_i(u) \wedge \mu B_i(v) \wedge \mu C_i(w) \wedge \mu D_i(x) \wedge \mu E_i(y)] \} \quad (3.11)$$

The order is changed as follows to take care of the max and min operations taken from different domain.

$$\mu E'(y) = \frac{\max}{1 \leq i \leq 36} \{ \frac{\max}{x} [\mu_{K'}(u, v, w, x) \wedge \mu A_i(u) \wedge \mu B_i(v) \wedge \mu C_i(w) \wedge \mu D_i(x)] \wedge \mu E_i(y) \} \quad (3.12)$$

$$\text{If the degree of fulfillment of the } i\text{th rule's antecedent is denoted by } \omega_i = \frac{\max}{x} [\mu_{K'}(u, v, w, x) \wedge \mu A_i(u) \wedge \mu B_i(v) \wedge \mu C_i(w) \wedge \mu D_i(x)] \quad (3.13)$$

The output fuzzy set of the linguistic model becomes

$$\mu E_i(y) = \frac{\max}{1 \leq i \leq 36} [\omega_i \wedge \mu E_i(y)] ; y \in Y \quad (3.14)$$

Going by these, the three steps involved in max-min (mamdani) inference are:

- a. Estimating the firing strength of the i th rule after aggregating the input (compute the degree of fulfillment)

$$\omega_i = \frac{\max}{x} [\mu_{K'}(u, v, w, x) \wedge \mu_{A_i}(u) \wedge \mu_{B_i}(v) \wedge \mu_{C_i}(w) \wedge \mu_{D_i}(x)] \text{ as in} \quad (3.13)$$

- b. Deriving the output fuzzy sets (By calculate the i th individual rule output)

$$E_i: \mu_{E'_i}(y) = [\omega_i \wedge \mu_{E_i}(y)] ; y \in Y, 1 \leq i \leq k \quad \text{as in} \quad (3.14)$$

- c. Aggregating the output fuzzy set

$$E'_i: \mu_{E'}(y) = \frac{\max}{1 \leq i \leq k} \mu_{E'_i}(y) , y \in Y \quad (3.15)$$

- d. Calculating the defuzzified output using:

$$\text{Centroid of Area (COA)} \quad {}^y\text{COA} = \frac{\sum \mu_{E'_i}(y)}{\sum \mu_{E'}(y)} \quad (3.16)$$

Stage 2: Transformation of Mamdani Fuzzy System to Sugeno Fuzzy System

The intent of the transformation is to produce an appropriate Sugeno FIS to the Mamdani FIS using optimization algorithms. Suppose the rules of the Sugeno FIS are of the form

$$R^i: \text{IF (antecedent) THEN } y^i = c_0^i + c_1^i x_1 + \dots + c_m^i x_m \text{ for each rule } i = 1..n \quad (3.17)$$

Where $y^i, \dots, y^n$ represent the consequents of each rule in the rule base and $\alpha^i, \dots, \alpha^n$ represent the firing levels of each rule. Then the equivalence between the two systems is given as

$$\text{Mamdani output} = \text{Sugeno output} \Leftrightarrow$$

$$\Leftrightarrow \text{Mamdani output} = \frac{\sum_{i=1}^n \alpha^i y^i}{\sum_{i=1}^n \alpha^i} \quad (3.18)$$

Where $y^i, \dots, y^n$ represent the consequents of each rule in the rule base and $\alpha^i, \dots, \alpha^n$ represent the firing levels of each rule.

Stage 3: Formulation of the Fuzzy Neural-Network Model

In order to provide training capability for the model such that it could adjust to the subjective decisions of various tutors on students observed or derived behaviours. The fuzzy student model is implemented in a connectionist adaptive network as Hybrid/Fused Neuro-Fuzzy System. The fuzzed neural network was built on the following principles:

- i. The number of cells in the input layer is equal to the number of input values
- ii. The number of cells in the fuzzification layer is equal to the number of fuzzy set
- iii. The number of cells in the premise layer, normalization layer and consequent layer is equal to the number of rules
- iv. The output layer has a single node for the final inference

The structure of the neural network for implementing the fuzzy student model for learning activities quantitative and qualitative exploration is shown in Figure 3.10.

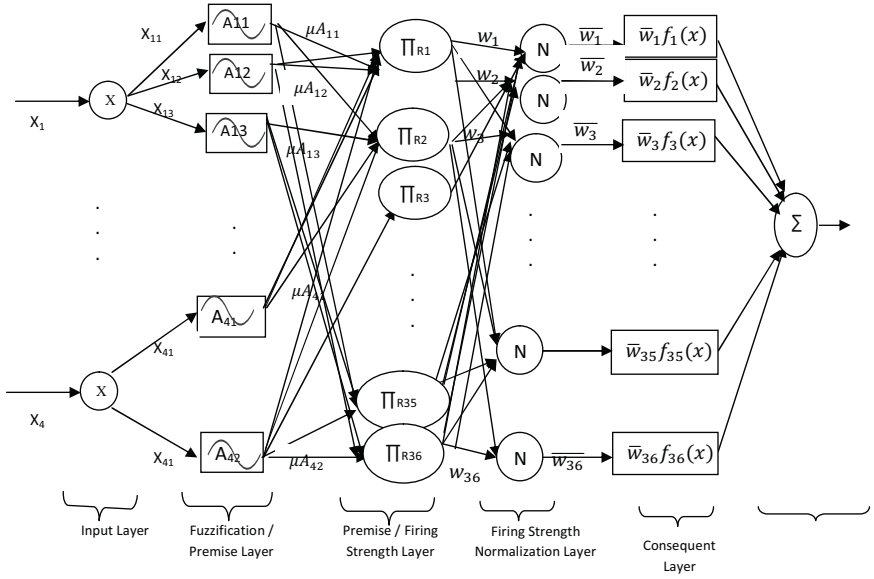


Figure 3.10: The Neuro-Fuzzy Model for Student Exploration and Concentration

The model is a six layer feed-forward hybrid network. As an adaptive network, it consists of nodes and directional links. The network is adaptive because some of the nodes have adjustable parameters; such nodes are indicated with circular/oval shape in the network. Other nodes in square /rectangle shape are fixed nodes.

The Input layer (L1) provides the system with the base value for each of the features contributing towards the evaluation of a particular feature of the students. For instance the total time spent on the course may be based on seconds say 10800s for a 3 hour course. So the input layer send out the external crisp values to the next fuzzification layer without any processing. Hence, the neurons in this layer passively transmit the external input (crisp) signals to the next layer. The output of layer1 is given as:

$$O_i^1 = x_i \quad (3.19)$$

The total number of neurons in the input layer is four (4), one each for four linguistic variables B1-B4. Hence, for every instance (a student), four crisp values will be available as input for the purpose of determining the status of the student.

The Fuzzification layer (L2) is the first hidden layer; it has node for every categories of expert's description and classification for each of the variables. Neurons in this layer represent antecedent fuzzy sets of the fuzzy rules. This design adopts low, medium, and high fuzzy set, for B1 and B3. It uses Non Adequate (NA), Adequate (A), Unsatisfactory (US) and Satisfactory (S) for B2 and B4 respectively. For each input value entering the system, the membership degree to which such input belongs will be estimated. Common functions are Bell shape, Triangular, Gaussian and Sigmoid. For this work the Gaussian transfer function was used because of its amenability to training via adjustment of the parameters.

$$\text{The Gaussian MF} = \mu_{A_{ij}}(x_j; C_{ij}, \sigma_{ij}) = e^{\left(\frac{-(x_j - c_{ij})^2}{2\sigma_{ij}^2}\right)} \quad (3.20)$$

Where x is the input, c is the centre and σ is the width, i is the input number and j is the terms number.

The output of the Fuzzification layer is the degree of membership of the input values. It can be given as:

$$O_{ij}^2 = \mu_{A_{ij}}(x_i) \quad (3.21)$$

The Premise layer (L3) is the second hidden layer. Each neuron in the layer corresponds to a fuzzy rule in the system. It receives signals only from relevant fuzzification neurons and calculates the activation of premises of the fuzzy rules. It uses minimum type t-norm to implement AND operators in each of the units. The t-norm operator for determining firing strength of each rule is given as:

$$O_j^3 = w_j = \prod_{i=1}^{36} \mu_{A_j}(x_i) \quad (3.22)$$

The fourth layer (L4) is the third hidden layer. Each neuron in this layer receives signals from all rule neurons in layer 3. It then calculate the normalized firing strength for a given rule to a close range [0 1]. It is given as:

$$O_j^4 = \bar{w}_j = O_j^3 / \sum_{j=1}^{36} O_j^3 = \prod_{i=1}^{36} \mu_{A_j}(x_i) / \sum_{j=1}^{36} \prod_{i=1}^{36} \mu_{A_j}(x_i) \quad (3.23)$$

The consequent layer is the defuzzification layer. Each neuron in this layer receives the initial input signals and connected to the respective normalization neuron in the preceding fourth layer. It adaptively multiplies O_j^4 with the consequent parameters as shown in (3.23).

$$O_j^5 = O_j^4 f_j(x) = \bar{w}_j f_j(x) = \bar{w}_j (p_j x_1 + q_j x_2 + r_j x_3 + s_j x_4 + t) \quad (3.24)$$

Here, the p , q , r , s , and t for each defuzzification neuron are the consequent parameters; they are to be determined by training. The x_1, x_2, x_3 , and x_4 are the initial inputs received.

The sixth layer is the output layer. This is a layer of single neuron that calculates the sum of the weighted consequent value from the defuzzification layer. For our model with 36 rules the overall output is given as:

$$O^6 = \sum_{j=1}^{36} \bar{w}_j f_j(x) = \sum_{j=1}^{36} \bar{w}_j (p_j x_1 + q_j x_2 + r_j x_3 + s_j x_4 + t_j) = y \quad (3.25)$$

Stage iv: The Network Training

The training techniques used for the network parameter identification is the Hybrid learning algorithm. It is a two pass algorithm; the forward pass and the backward pass. This option is opted for because the use of back propagation (Steepest Descent Method) - a one pass algorithm alone as shown in Table 4.2b converges with high error estimates. The hybrid learning uses combines Steepest Descent (SD) with Least Squares Estimation (LSE). This learning method is possible because output of the adaptive network is linear in some of the network's parameters as shown in (3.23) and (3.24). The two passes of the Hybrid learning algorithm is known as forward propagation and backward propagation. In the forward pass, on the condition that the premise (nonlinear) parameters are fixed, the input vector is propagated through the network layer by layer until the last layer in which the consequent parameters are estimated by linear Least-Square Method. The sum of squared residuals or the sum of squared errors is given as:

$$\text{The Sum of Squared Error} = \sum_{i=1}^{36} (y_i - y_i^*)^2 \quad (3.26)$$

Where y_i is the desired output and y_i^* is the observed output from the system. The essence of squaring the errors is to prevent cancellation of error value with opposite signs, thereby gives the sum of error made by the network in the course of identifying the training dataset. The network error is a function of the weight (w) of the network. If the error is unsatisfactory, the network weight needs to be adjusted in a manner to minimize the error. This can be achieved by using Gradient

descent method. The Gradient descent method is ‘a going downhill in small steps’ method until the bottom of the error surface is reached. As a back propagation technique, the weight update of Gradient descent is scaled by a learning rate η as show in (3.27).

$$w_{ji \text{ new}} = w_{ji \text{ old}} + \eta(y_j - y_j^*)x_i \quad (3.27)$$

The w_{ji} represents the synaptic weight to j^{th} neuron in the output layer from the i^{th} neuron in the preceding layer. The parameter η is the speed at which error correction is made. Since changing the weight value could lead to convergence or divergence from the local minima of the curve. It is essential therefore to take steps proportional to the negative of the gradient at the point of estimation.

3.3. Models Implementation and Open Source Integration

Each of the stages in the Neuro-Fuzzy Network development as discussed in section 3.2.4 where simulated in the MATLAB environment. After satisfactory performance it was integrated in Moodle LMS in the pattern discussed in section 3.1.3. The following are the descriptions of the implementations.

3.3.1 Mamdani Fuzzy Model Simulation

MATLAB Version 7 was used to simulate the Fussy Inference System (FIS). The FIS Editor was launched from the command prompt by executing the `>> fuzzy` command.

The parameters were set accordingly. *And Method* = min, *Or Method*= max, *implication* = min, *Aggregation*= max, *Defuzzification* = centroid, *FIS Type* = Mamdani, *FIS Name* = E_LearningUsers.

The descriptions of the membership function (MF) for the four inputs were defined as follows: The Completion variable: *Type*= gaussmf; Linguistic term

NonAdequate = 0 – 45; Linguistic term *Adequate* = 45– 100; *Range* = [0 100];
Display Range = [0 100].

The Reading Time variable: *Type*= gaussmf; Linguistic term *Low* = 0 –30;
Linguistic term *Medium* 30– 70; Variable *High* 70– 100, *Range* = [0 100]; *Display*
Range = [0 100].

The Assessment variable: *Type*= gaussmf; Linguistic term *Unsatisfaction* = 0 –
45; Linguistic term *Satisfaction* = 45– 100; *Range* = [0 100]; *Display Range* = [0
100].

Participation Index variable: *Type*= gaussmf; Linguistic Variable *Low* = 0 – 30;
Linguistic term *Medium* 30– 70; Linguistic term *High* 70– 100, *Range* = [0 100];
Display Range = [0 100].

The Rule Editor was used to define the thirty six (36) rules estimated from
Decision Tree and outlined in the Rule Table as in [Table 3.3]. Equal weight of one
(1) was assigned to each of the rules.

The Simulating interface for the E-learning Users Fuzzy Inference System is as
shown in Figure 3.11.

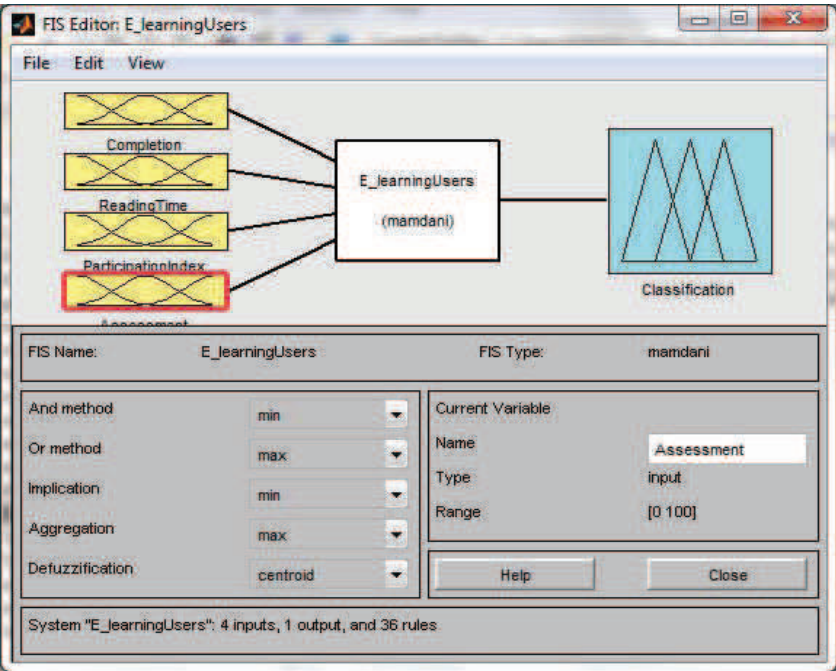


Figure 3.11: Formulation of Mamdani FIS Model

The Simulating interface for the E-learning Users Fuzzy Inference in Figure 3.11 shows the input variables, their types and ranges. It also revealed the setting for the fuzzy operators and defuzzification method used.

The coding for FIS is as follows:

[System]

Name='E_learningUsers'

Type='mamdani'

Version=2.0

NumInputs=4

NumOutputs=1

NumRules=36

AndMethod='min'

OrMethod='max'

ImpMethod='min'

AggMethod='max'

DefuzzMethod='centroid'

[Input1]

Name='Completion'

Range=[0 100]

NumMFs=2

MF1='NonAdequate': 'gaussmf', [15 0]

MF2='Adequate': 'gaussmf', [20 101.516793066089]

[Input2]

Name='ReadingTime'

Range=[0 100]

```
NumMFs=3
MF1='Low':gaussmf,[15 0]
MF2='Medium':gaussmf,[9.93789322113826 50]
MF3='High':gaussmf,[15 100]
```

```
[Input3]
Name='ParticipationIndex'
Range=[0 100]
NumMFs=3
MF1='Low':gaussmf,[15 0]
MF2='Medium':gaussmf,[15 50]
MF3='High':gaussmf,[15 100]
```

```
[Input4]
Name='Assessment'
Range=[0 100]
NumMFs=2
MF1='Unsatisfactory':gaussmf,[15 0]
MF2='Satisfactory':gaussmf,[20 100]
```

```
[Output1]
Name='Classification'
Range=[0 100]
NumMFs=2
MF1='Repeat':gaussmf,[15 0]
MF2='Proceed':gaussmf,[20 100]
```

Some of the [Rules]

1 1 1 1, 1 (1) : 1

1 1 1 2, 1 (1) : 1

1 1 2 1, 1 (1) : 1

1 1 2 2, 1 (1) : 1

1 1 3 1, 1 (1) : 1

3.3.2. Sugeno Fuzzy Model Simulation

Similarly, The Sugeno Fuzzy Inference System equivalent was generated using the following commands. As shown in Figure 3.12, the Sugeno Fuzzy has the same premise as the Mamdani but the consequent is in the form of First Order Polynomial. The MATLAB command used for the transformation is

```
>> a=readfis('e_learningusers')  
>> sugenoelearningusers=mam2sug(a)
```

3.3.3. Neuro-Fuzzy Model Simulation

The Sugeno FIS Model was converted to its Adaptive Neuro-Fuzzy Inference System (ANFIS) equivalent with the command:

```
>> anfisedit e_learninguserssugeno
```

The generated ANFIS during the training session is as shown in Figure 3.13.

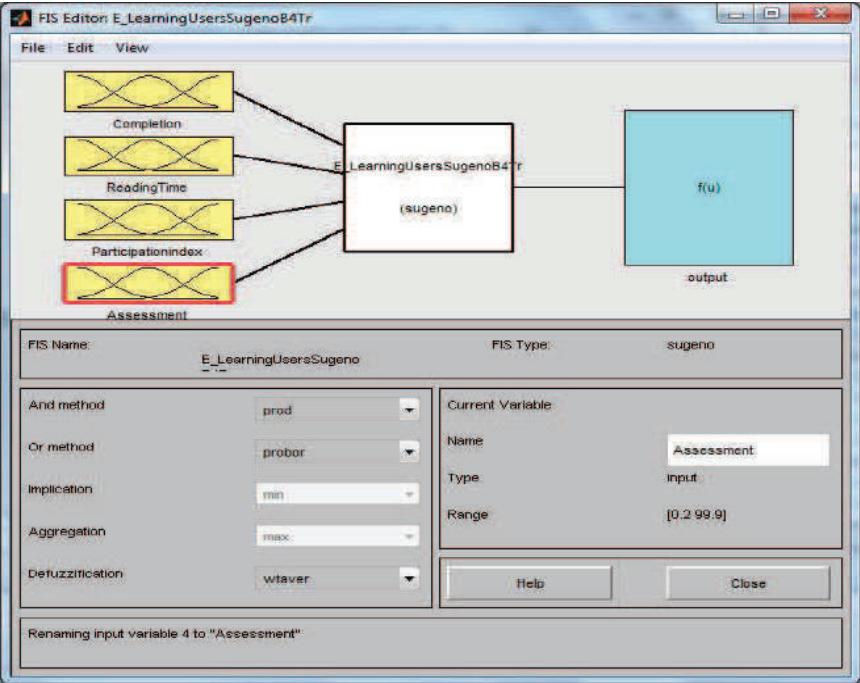


Figure 3.12. Formulation of Sugeno Fuzzy FIS Model

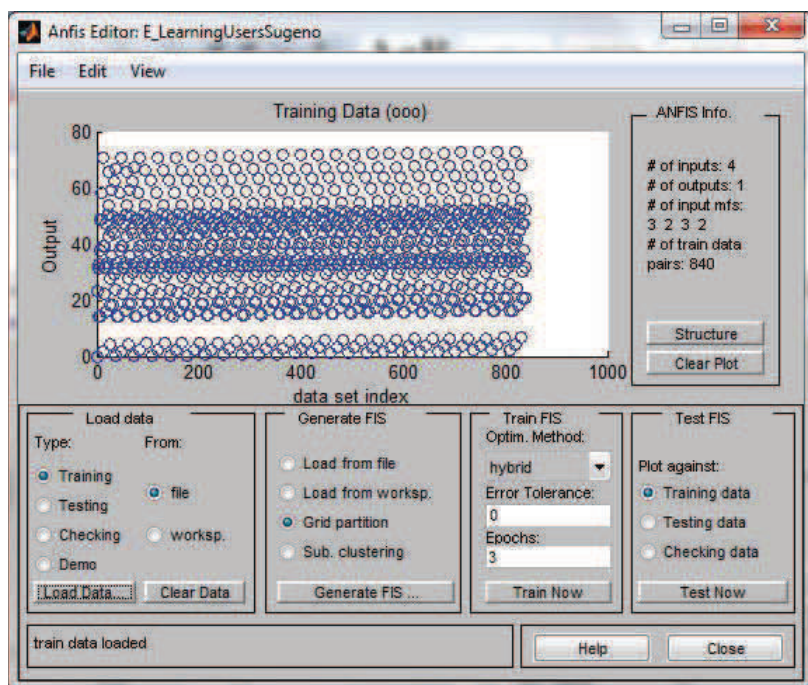


Figure 3.13: ANFIS Editor for E-learning Users Model

The model of the ANFIS Editor used is as shown in Figure 3.14. The figure revealed the ANFIS design information, and the current setting for the Load data, data partitioning approach, the optimization method and the plotted structure. The system codes are:

[System]

Name='E_LearningUsersSugenoAfterTr'

Type='sugeno'

Version=2.0

NumInputs=4

NumOutputs=1

NumRules=36

AndMethod='prod'

OrMethod='probor'

ImpMethod='prod'

AggMethod='sum'

DefuzzMethod='wtaver'

[Input1]

Name='input1'

Range=[0 99.7]

NumMFs=3

MF1='in1mf1': 'gaussmf', [14.5608671662949 0.0416599154960089]

MF2='in1mf2': 'gaussmf', [14.7631624437696 33.9109810968652]

MF3='in1mf3': 'gaussmf', [14.3471000691889 67.7327393467354]

[Input2]

Name='input2'
Range=[0 99.9]
NumMFs=2
MF1='in2mf1': 'gaussmf',[41.5926862218851 0.135744287752947]
MF2='in2mf2': 'gaussmf',[41.4875380772901 97.3840750009157]

[Input3]
Name='input3'
Range=[0.2 99.8]
NumMFs=3
MF1='in3mf1': 'gaussmf',[17.548311929502 0.0208828036419895]
MF2='in3mf2': 'gaussmf',[17.715798832316 41.3605619761853]
MF3='in3mf3': 'gaussmf',[17.5290598396276 82.5396810154334]

[Input4]
Name='input4'
Range=[0.2 99.9]
NumMFs=2
MF1='in4mf1': 'gaussmf',[33.2285025717858 0.191900972602624]
MF2='in4mf2': 'gaussmf',[32.977662235064 77.6649167223241]

[Output1]
Name='output'
Range=[9.4 92.9]
NumMFs=36
MF1='out1mf1': 'constant',[-2.19302390058667]
MF2='out1mf2': 'constant',[24.7013372347611]

MF3='out1mf3': 'constant', [10.2571088316122]
 MF4='out1mf4': 'constant', [32.5317139043132]
 MF5='out1mf5': 'constant', [24.9942668241128]
 MF6='out1mf6': 'constant', [42.5912606207866]
 MF7='out1mf7': 'constant', [23.7888339243892]
 MF8='out1mf8': 'constant', [42.2792251917189]
 MF9='out1mf9': 'constant', [34.0812936255797]
 MF10='out1mf10': 'constant', [56.4595323638787]
 MF11='out1mf11': 'constant', [47.6322312629381]
 MF12='out1mf12': 'constant', [68.4312113965412]
 MF13='out1mf13': 'constant', [7.73036194131818]
 MF14='out1mf14': 'constant', [29.8637108139432]
 MF15='out1mf15': 'constant', [16.9847595062718]
 MF16='out1mf16': 'constant', [38.4174596530992]
 MF17='out1mf17': 'constant', [27.841743477347]
 MF18='out1mf18': 'constant', [51.6235617322364]
 MF19='out1mf19': 'constant', [35.9846725222968]
 MF20='out1mf20': 'constant', [50.0140795795939]
 MF21='out1mf21': 'constant', [39.9786032571165]
 MF22='out1mf22': 'constant', [64.1141567923862]
 MF23='out1mf23': 'constant', [52.5913581877894]
 MF24='out1mf24': 'constant', [73.5111206423128]
 MF25='out1mf25': 'constant', [21.535818306578]
 MF26='out1mf26': 'constant', [44.1025470347981]
 MF27='out1mf27': 'constant', [27.4287508823844]
 MF28='out1mf28': 'constant', [52.8279364592846]
 MF29='out1mf29': 'constant', [47.9038979707299]

MF30='out1mf30': 'constant', [60.8293199903685]
MF31='out1mf31': 'constant', [40.4248631852286]
MF32='out1mf32': 'constant', [66.2257490420027]
MF33='out1mf33': 'constant', [55.8276434799825]
MF34='out1mf34': 'constant', [73.549286380363]
MF35='out1mf35': 'constant', [61.0611487457285]
MF36='out1mf36': 'constant', [89.0490629454362]

[Rules]

1 1 1 1, 1 (1) : 1
1 1 1 2, 2 (1) : 1
1 1 2 1, 3 (1) : 1
1 1 2 2, 4 (1) : 1
1 1 3 1, 5 (1) : 1
1 1 3 2, 6 (1) : 1
1 2 1 1, 7 (1) : 1
1 2 1 2, 8 (1) : 1
1 2 2 1, 9 (1) : 1
1 2 2 2, 10 (1) : 1

The model's structure is as shown in Figure 3.14. The models rule viewer is as shown in Figure 3.15.

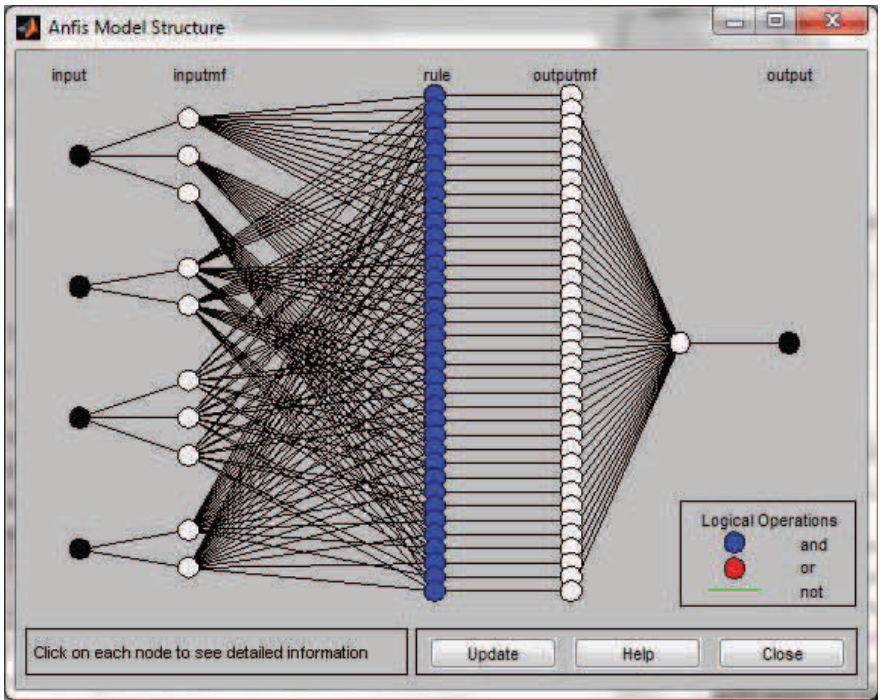


Figure 3.14: Generated Neuro-Fuzzy Structure for the E-learning Users Model

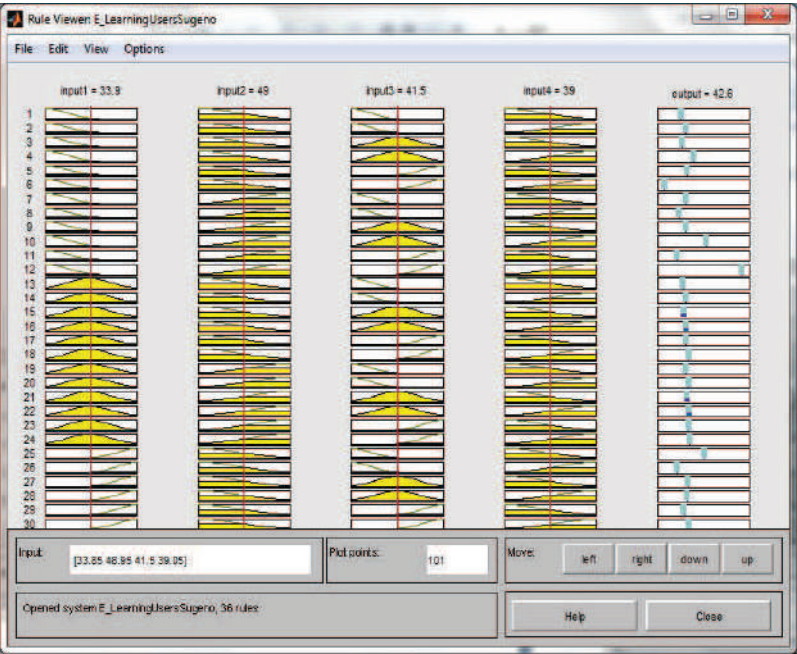


Figure 3.15. A Rule Viewer for the E-learning Users Model

The system auto-generated fuzzy inference structure shown in Figure 3.14 is the equivalent of the structure in Figure 3.10. The figure shows the four neurons of the input layer, one for each of the input variables. The second layer shows the ten (10) fuzzification neurons, one for each of the fuzzy-terms. The third or premise layer has the thirty six ($3 \times 2 \times 3 \times 2$) neurons, one for each of the rules. The blue colour shows that 'AND' is the aggregation operator used. The thirty six normalization neurons and the thirty six consequent neurons in Figure 3.10 are merged in Figure 3.14. Finally, the single neuron for the inference or output is shown. Unlike Figure 3.10 where certain details of the neurons are revealed, to view details of Figure 3.14 requires mouse pointing to the desired components. Figure 3.15 is the rule viewer for the E-learning Users Model. The Rule viewer is an interface for evaluating input. It could be done by direct typing of the four input values or by dynamically adjusting the red transverse lines in each of the variables.

3.3.4. Activities Evaluation Panel Interface Operations

Additionally, a Neuro Fuzzy Learner's Activities Evaluation Panel Interface was designed for the teacher to monitor the class progress. The panel as shown in Figure 3.16 is for the teacher to determine students' status. To actualize this, the teacher may type in the identification number of a student to view the current status of such student. The status of the whole class may as well be viewed by selecting the file that contains the class list. Whatever choice made in the 'learner info' section will activate and display the current learner's aggregate values. Finally, when the 'Perform Evaluation' button is clicked, the classification value and the equivalent remarks will be displayed. In the remarks, 1 represent Proceed, on the other hands 2 represent repeat.

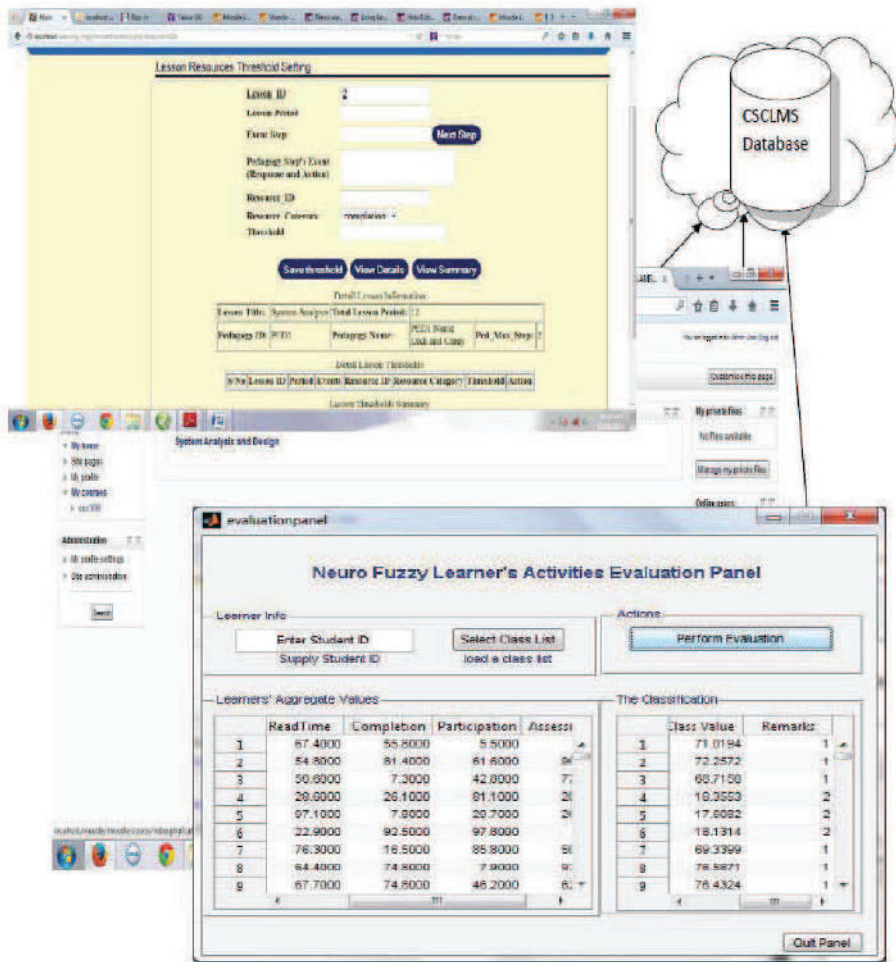


Figure 3.16. The Evaluation Panel in Relation with Moodle and Pedagogy Interfaces

The combined interfaces shown in Figure 3.16 depict the actual relationship between the Moodle, Pedagogy and Evaluation panels interfaces. The source and destination of all activities on these interfaces is the moodlelms database. This architecture makes it possible to synchronize all that is going between the teacher-lesson, lesson-student and student-teacher interactions.

3.3.5 Dataset Generation and Model Evaluation

The accuracy and efficiency of the formulated models needs to be determined, first to ascertain the correctness and adequacy of the models for the intended purpose. To actualize this, dataset is required. Unfortunately, however, it was discovered that public dataset that satisfy the four variables (Reading Time, Completion Rating, Participation Index and Assessment Score) being considered in this study were not readily available. To this end, dataset were initially simulated before the completion of the time required to gather live dataset from www.cscslams/moodle platform. Generally, simulated dataset are commonly used in educational related research, just as it is used in medicine or medically related research, the goal is to facilitate evaluation of models and systems in the earlier stage of development. Furthermore, simulated dataset are sometimes adopted with the intent of preventing any perceived abuse of human rights that may be as associated with exposing personal information to the public. The techniques used in articulating the two forms of datasets (the simulated and the live) for model evaluation are as follows.

3.3.5.1 Data Generation - Simulated Dataset Approach

Data simulation for research purpose is necessitated either by inadequate volume of dataset or absolute absent of suitable dataset for the domain being modelled. The intent in the former case might be for instance, to blow up the size of

the dataset for effective operations of a particular classifier. In such a case, some statistical parameters drawn from the available data would be required. So, in line with the concept of “reverse” statistics, required volume of simulated dataset can be generated where the statistical value such as mean, variance, standard deviation etc are known. In Statistical Package for Social Sciences (SPSS) a variety (over thirty) of random variates for specified distribution are available. Examples of such functions are NORMAL(stddev), UNIFORM(max, min), RV.POISSON(mean) or RV.LAPLACE(mean,scale). The choice depends on the type of distribution required. Similarly, in MATLAB functions such as rand(), randi(), randn() and randperm() are available for creating array of random numbers. Furthermore, Microsoft Excel also has tools for executing substantial simulation, without cumbersome processing tricks or VBA coding.

The required dataset simulation used in this work is of the second type. The dataset were formulated firstly by selecting the membership function for the four input variables and output variable as the structure that underlines the dataset. Secondly, the dataset was generated using the random number generator in the Microsoft Excel data analysis tools. Ten thousand (10,000) unique simulated dataset was generated. The figure is ten folds of one thousand (1,000) which is the number of unique values between 0.1 and 100 at interval of 0.1. From the 10,000 by 4 matrix dataset formulated the top ten percent (1000 records) was selected for the model evaluation. The selected 10% was further subdivided to ratio 70:15:15. The ratio is the standard recommended in MATLAB. The first 70% (700) was designated as Educational dataset for training, one of the remaining 15% (150) as validation dataset and the last 15% (150) as testing dataset. The composition of simulated dataset and sample dataset are shown in Figure 3.17 and 3.18 respectively.

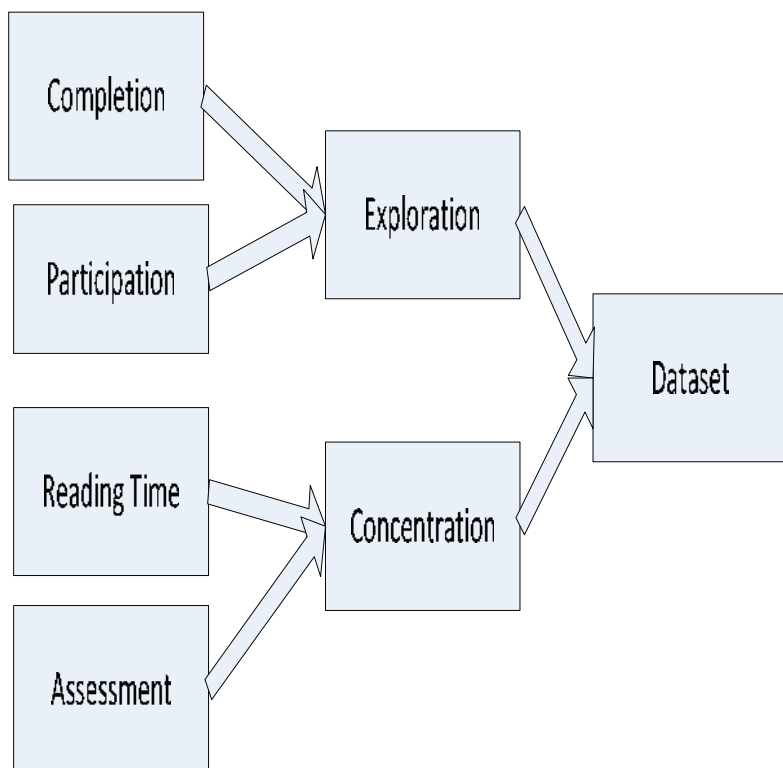


Figure 3.17: Composition of the Simulated Dataset

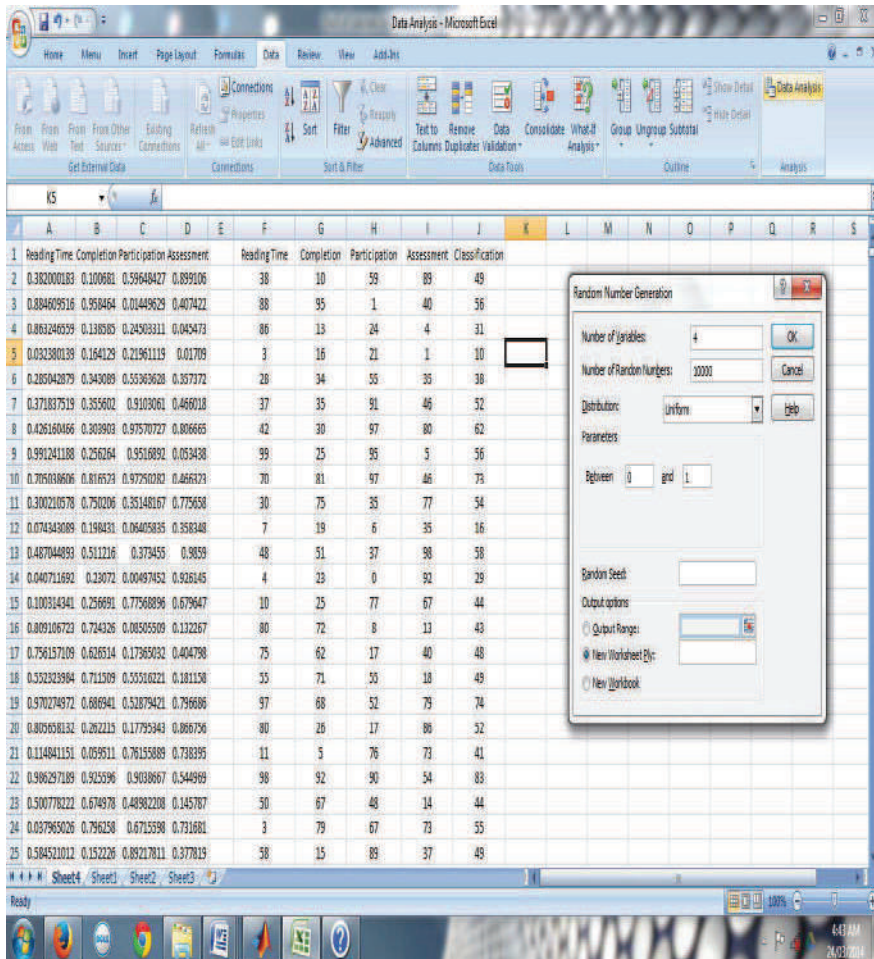


Figure 3.18: The Simulation Data Set Generation Interface

The formulated dataset is analogous of the Transformed / Aggregated Activity Log in the Control layer of the Actuator Indicator Model in Figure 3.7. The composition in Figure 3.17 shows the four linguistic variables in pairs as they lead to the two observable behaviours which constitute the dataset. The samples of the actual dataset generated and the Random Number Generator interface are as shown in Figure 3.18.

3.3.5.2 Data Generation – Live Dataset Approach

In the Rain Semester of 2013-2014 academic sessions, sixty (60) B.Sc Computer Science students in the Department of Computer, Library and Information Science, Kwara State University, Malete enrolled for CSC 306 on the enhanced Moodle platform. The course titled System Analysis and Design is accessible on www.csclams.net. The lesson which spans for period of fourteen weeks entails utilization of several learning activities and resources as provided in Moodle LMS. The breakdown of the course for the duration is as shown in Table 4.5. Moodle by defaults logs (stores) users and details of all their activities into corresponding mdl_tables. The mdl_user table stores one record for each user in the system. In all it has sixty five (65) users, five (5) for the Admin and the Teachers, the remaining sixty (60) are students records. The summaries of data elicited from other specified mdl_tables in relation to the four inputs for the model are as follows. The codes for these estimations are as in Appendix A:

Time Variable Estimation

The estimation of the total time spent by the student on the platform throughout the duration is the most challenging of all. The mdl_log table logged every user's actions as far as possible. The mdl_log table for this research has the total of twenty thousand seven hundred and seventy four (20,774) records. The

attributes considered in the table are userid, time, ip, course and action. Four patterns of usage (online sessions) were identified:

- a. Login-logout session: here the user successfully logged out after series of actions. This is the ideal and expected situations. The time spent in such session is given as $T_{logout} - T_{login}$. The sum of all such time is given as:

$$\sum_{i=1}^p (T_{logout} - T_{login}) \quad (3.28)$$

- b. Login-login session: here the user could not log out of the session as expected. This situation may be as result of Internet connectivity failure or care-free attitude. In that case, the time of the last valid action that precedes the second login following the first is considered as the logout time for that session. The time spent in such session is given as $(T_{login2-2}) - T_{login1}$. The sum of all such time is given as: $\sum_{j=1}^q ((T_{login2} - 2) - T_{login1})$ (3.29)

- c. Login_ip - logout_ip session: this is the kind of situation in which a login or a logout is indicated by a change in the internet protocol (ip) addresses. Hence, the end of a previous session (which is also the beginning of a new session) is signified by the difference in the successive ip addresses. The time spent in such session is given as $T_{logout_ip} - T_{login_ip}$. The sum of all such time is given as:

$$\sum_{k=1}^r ((T_{logout_ip} - T_{login}) + (T_{logout_ip} - T_{login_ip})) \quad (3.30)$$

- d. Login_in - logout_end session: this category of session represent a situation when the last action for a student's record set in the mdl_log is not a logout. The time spent in such session is given as $T_{logout_end} - T_{login}$. The sum of all such time is given as:

$$\sum_{t=1}^s (T_{logout_end} - T_{login}) \quad (3.31)$$

The total time spent by the student in relation to the threshold was given in (3.1) as $x_t = \frac{\sum te}{T} \times 100$, where $\sum te$ is the total time spent by the learner on the lesson and T is the total threshold for the time in seconds. From this equation,

$$\begin{aligned} \Sigma te = & \Sigma_{i=1}^p (Tlogout - Tlogin) + \Sigma_{j=1}^q ((Tlogin2 - 2) - Tlogin1) + \\ & \Sigma_{k=1}^r ((Tlogout_{ip} - Tlogin) + (Tlogout_{ip} - Tlogin_{ip})) + \\ & \Sigma_{l=1}^s (Tlogout_{end} - Tlogin) \end{aligned} \quad (3.32)$$

Where p,q,r and s are the upper bounds for their respective type of sessions. The i,j,k and l are the counters for the various sessions.

Completion Variable Estimation

The table that stores the completion state (completed or non_ completed) of all modules specified by the teacher against all registered students is the mdl_course_modules_completion table. The attributes considered in this table are userid, coursemoduleid and completionstate. The total instance of module completion status in this lesson is four hundred and sixty eight (468), out of this number four hundred and forty nine (449) had completed status (1) while the status of nineteen (19) of them are non_ completed (0).

The completion value for a student is estimated based on the equation $x_c = \frac{\Sigma Ce}{C} \times 100$ as in (3.2) where ΣCe is the total number of modules_completion records with ‘completed status’ that is available for the student and the C is the completion threshold set by the teacher. The completion status would either be classified as either Non_Adequate or Adequate based on whether the value is within the range of 0: 45 or greater than 45.

Participation Index Variable Estimation

The measure for student participation in a lesson is a composite function. In this research, participation is treated as a function of assignment submission, approved project proposal, survey participation, message initiation and reply, and forum

post. The mdl_assign_submission is the log table for monitoring student assignment submission. The attributes considered include userid, assignment_id and the assignment_statusfields which could either be submitted (1) or draft (0). The total number of submissions in this table is two hundred and fifty seven (257), the number with submitted status is two hundred and fifty six while the status of only one record reads draft. The mdl_data_records table is used for database. It is used in this work to process the projects topics submitted by the students. The attributes used include userid, dataid, and approval. A submission that is approved has its status set to 1 otherwise it is set to 0. The table has fifty seven (57) submissions, fifty three (53) are approved while four (4) are not approved. The total number of students that participated in the survey is forty five (45); this is as shown in the mdl_feedback_tracking table. The mdl_message_read table has three hundred and thirty records (330), two hundred and eighty one (281) of them had notification status 1 meaning they are system notifications. The forty nine (49) of them with notification status 0 are included in our estimation because they are the messages exchanged between students. Finally, students' forum posts are included in the participation index. The mdl_forum_post table logs the record of students' forum threads either as parent or as children. The total number of forum threads is thirty four (34). The students that participated in messaging and forum would have the points included in their grading. If u,v,w,x,y, is used respectively for tables mdl_assign_submission, mdl_data_records, mdl_feedback_tracking, mdl_message_read and mdl_forum_post. The total participation index for a student x can be estimated using $x_p = \frac{\sum pe}{p} \times 100$ as in (3.3). Where the $\sum pe = \sum u, v, w, x, y$

$$(3.33)$$

Diagnosis Assessment Estimation

The students Diagnosis Assessment is extracted from the mdl_quiz_grades. The table has the quiz value for all students that participated in the quiz. The overall quiz grade incase of more than one can be estimated using $x_d = \frac{\sum q}{Q} \times 100$ as in (3.3)

3.4 Fuzzy and Neuro-Fuzzy Models Evaluation

The three types of models (Mamdani, Sugeno and ANFIS) were evaluated using the following algorithms.

3.4.1 Algorithm for Mamdani Fuzzy Model Evaluation

The Mamdani fuzzy Model which was named as e_learningusers was evaluated using a dataset saved as testingdataset.dat. the algorithm is:

```
>> fismat=readfis('e_learningusers')%read the saved e_learningusers.fis
fismat =
name: 'E_learningUsers'
type: 'mamdani'
andMethod: 'min'
orMethod: 'max'
defuzzMethod: 'centroid'
impMethod: 'min'
aggMethod: 'max'
input: [1x4 struct]
output: [1x1 struct]
rule: [1x36 struct]
>> load testingdataset.dat % load the testing data set
```

```
>> evalfis(testingdataset, fismat) %the evaluation command for fismat=
e_learningusers'
```

3.4.2 Algorithm for Sugeno_Fuzzy Model Evaluation

The name of the Sugeno_Fuzzy Model is e_learningusersssugeno and the testing data is testingdataset.dat which is the same file used for the Mamdani model.

```
>> >> fismat= readfis('e_learningusersssugeno')

fismat =
name: [1x21 char]
type: 'sugeno'
andMethod: 'prod'
orMethod: 'probor'
defuzzMethod: 'wtaver'
impMethod: 'prod'
aggMethod: 'sum'
input: [1x4 struct]
output: [1x1 struct]
rule: [1x36 struct]

>> load testingdataset.dat % load the testing data set
>> evalfis(testingdataset, fismat) % evaluation fismat =
e_learningusersssugeno'
```

3.4.3 Algorithm for ANFIS Model Evaluation

The Neuro_Fuzzy model file is saved as 'e_learninguserssugenoaftertr' to mean the trained Sugeno Fuzzy based Neural Network. Its testing dataset is the same as that used for the previous two models.

```
>> fismat = readfis('e_learninguserssugenoaftertr')

fismat =

name: 'E_LearningUsersSugenoAfterTr'
type: 'sugeno'
andMethod: 'prod'
orMethod: 'probor'
defuzzMethod: 'wtaver'
impMethod: 'prod'
aggMethod: 'sum'
input: [1x4 struct]
      output: [1x1 struct]
rule: [1x36 struct]
>> load testingdataset.dat           % load the testing data set
>> evalfis(testingdataset, fismat)   %      evaluation      fismat      =
e_learninguserssugenoaftertr'
```

3.4.4 Performance Evaluation Metrics

The efficiency of the model was determined using both classification uncertainty metrics and confusion matrix-based metrics. The classification uncertainty metrics considered are Mean Absolute Error (MAE) and Root Mean-Squared Error

(RMSE). The confusion matrix-based metrics used are Accuracy, Precision and Recall. The details of these metrics are as follows.

3.4.4.1 The Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) is the average of the difference between predicted and the actual value in all test cases. It is the average prediction error. It is usually used to measure the typical spread of data around the regression line. Suppose the actual output is given as a , and the expected output is c , the formula for calculating MAE is:

$$\frac{|a_1 - c_1| + |a_2 - c_2| + |a_3 - c_3| + \dots + |a_n - c_n|}{n} \quad (3.34)$$

3.4.4.2 The Root Mean-Squared Error (RMSE)

The Root Mean-Squared Error (RMSE) is a frequently used measure of differences between values predicted by a model or estimator and the values actually observed (expected) values. It is the square root of the mean square error (Ardil and Sandhu, 2010). The formular is given as:

$$\sqrt{\frac{(a_1 - c_1)^2 + (a_2 - c_2)^2 + (a_3 - c_3)^2 + \dots + (a_n - c_n)^2}{n}} \quad (3.35)$$

3.4.4.3 The Accuracy

The system accuracy is measured by the fraction of the number of correct prediction over the total number of predictions. These counts can be tabulated into a Confusion Matrix or Contingency table having the predicted classes in the rows and the true classes in the column. The Confusion Matrix indicates the behaviour of the classifier for individual class. The accuracy of each of the model and their corresponding Confusion Matrix are shown in Table 4.4a and Table 4.4b. The accuracy is given as:

$$Accuracy = \frac{TP+TN}{P+N} \quad (3.36)$$

TP- True Positive: Positive examples that is correctly classified as positive by the model

TN-True Negative: Negative examples that is correctly classified as negative by the model

P- Positive: Total positive examples in the model

N- Negative: Total negative examples in the model

3.4.4.4 The Precision

The Precision of a system is the proportion of selected items that the system got right. It is a good metric for unbalanced dataset and for a domain where detection of one class is considered much more important. The Precision estimates for the models are as shown in Table 4.4a it is calculated as:

$$Precision = \frac{TP}{TP+FP} \quad (3.37)$$

3.4.4.5 The Recall

The Recall is a measure of the proportion of the number of items the system selected as positive to the total number of true positive and false negative. The Recall estimates for the models are as shown in Table 4.4a. The formular is given as:

$$Recall = \frac{TP}{TP+FN} \quad (3.38)$$

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Classification Uncertainty and Complexity Performance Measures

The efficiency of the Neuro-Fuzzy model was determined by using classification uncertainty, model complexity and confusion matrix-based metrics. The complexity was measured based on training time, epochs, training error, training data error and validation data error. Finally, the model's prediction accuracy was measured using confusion matrix based metrics - Accuracy, Precision and Recall.

The analyses in tables 4.1a, 4.1b, 4.2a, 4.2b, 4.3a and 4.3b were based on MAE and RMSE. The analyses are for the purpose of experimentally determining the optimal parameter combinations for the model. These metrics estimates the performance absolute error values in which lower value indicates a better model. The result of the model's complexity measurement is shown in Table 4.3c.

The results of complexity performance are system specific. The complexity experiment was carried out on MATLAB R2010G, Version 7.10, 32-bit (Win 32) with License Number 161051. The specifications of the Computer System used are:

Manufacturer: Dell;	Model: N5050
Hardware Capacity 500GB;	Free Space 338GB
Processor: Intel (R) Core TM i3.2350m; CPU @ 2.30 GHz	
Installed Memory (RAM): 4.00 GB; System Type: 64-bit Operating System	
Operating System: Windows 7, Home Premium, Service Pack I	

Table 4.1a is the Mamdani Fuzzy Model output based on five defuzzification methods. The evaluations of these models are as shown in Table 4.1b.

Table 4. 1a: Mamdani Fuzzy Model Output By Defuzzification Methods

S/No	Input Variables				Expected Output	Mamdani Fuzzy Systems Output				
	Reading	Completion	Participation	Assessment		Centroid	Bisector	MOM	LOM	SOM
1	67.4	55.8	5.5	52	73.0	71.0	72	76	100	52
2	54.8	81.4	61.6	96.3	74.1	72.3	73	77	100	54
3	50.6	7.3	42.8	77.4	71.2	68.7	70	75	100	50
4	28.6	26.1	81.1	20.5	16.5	18.4	17	14	28	0
5	97.1	7.8	29.7	26.9	15.9	17.6	17	13	26	0
6	22.9	92.5	97.8	29	16.9	18.1	18	14.5	29	0
7	76.3	16.5	85.8	50.3	71.9	69.3	71	75.5	100	51
8	64.4	74.8	7.9	97.4	78.4	76.6	77	81.5	100	63
9	67.7	74.8	46.2	62.5	78.3	76.4	77	81.5	100	63
10	45.4	82.2	24.3	64.1	63.1	57.3	60	72	100	44
11	25.3	13.4	42	4.3	15.1	16.7	16	12.5	25	0
12	44.5	77.4	62.7	71.2	60.5	54.0	56	71.5	100	43
13	54.8	20.6	92.1	63.7	74.1	72.3	73	77	100	54
14	60.3	76.5	40.7	67.8	76.8	74.9	76	79.5	100	59
15	2.4	74.7	9.3	61.3	16.8	18.0	18	14.5	29	0
16	56.4	12	89.1	76.5	74.9	73.1	74	77.5	100	55
17	57.6	37.9	16.9	97.4	75.4	73.7	74	78.5	100	57
18	20.2	58.6	75.4	21.3	14.8	16.4	16	12	24	0
19	66.9	12.6	79.6	61.5	78.0	76.0	77	81	100	62

					Precision Accuracy Measures					
						Centroid	Bisector	MOM	LOM	SOM
						MAE	6.3	37.5	429.1	420.9
						RMSE	2.6	6.2	20.8	20.6

Centroid			Bisector			Middle of Maximum			Largest of Maximum			Smallest of Maximum			
S/N	Centro	a-c	(a-	Bisec	a-c	(a-	Mo	a-c	[a-	Lom	a-c	(a-c)^2	Som	a-c	[a-c]^2
1	71.0	2.0	3.9	72	1.0	1.0	76	3.0	9.0	100	27.0	728.7	52	21.0	441.3
2	72.3	1.8	3.3	73	1.1	1.2	77	2.9	8.5	100	25.9	671.5	54	20.1	403.4
3	68.7	2.5	6.4	70	1.2	1.5	75	3.8	14.2	100	28.8	827.2	50	21.2	451.1
:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:
147	17.6	1.6	2.5	17	1.0	0.9	13.	2.5	6.5	27	11.0	120.0	0	16.0	257.4
148	39.4	7.9	62.5	34	2.5	6.5	21	10.5	109.3	42	10.5	111.2	0	31.5	989.3
149	60.9	5.1	25.6	64	2.0	3.9	73	7.0	49.4	100	34.0	1157.9	46	20.0	398.9
150	24.0	8.7	75.5	15	0.3	0.1	7	8.3	69.6	14	1.3	1.8	0	15.3	235.4
		483.2	2483.		230.	933.1		707.4	5615.3		2691	64360.		2850.	63123.
		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$
		(MAE)	(MAE)		(MAE)	(MAE)		(MAE)	(MAE)		(MAE)	(MAE)		(MAE)	(MAE)
		3.3	16.6		1.6	6.3		4.8	37.5		18	429.1		19.1	420.9
		$=\sum(a-c)/n$	$=\sum(a-c)^2/n$		$=\sum(a-c)/n$	$=\sum(a-c)^2/n$		$=\sum(a-c)/n$	$=\sum(a-c)^2/n$		$=\sum(a-c)/n$	$=\sum(a-c)^2/n$		$=\sum(a-c)/n$	$=\sum(a-c)^2/n$
		(RMSE)	(RMSE)		(RMSE)	(RMSE)		(RMSE)	(RMSE)		(RMSE)	(RMSE)		(RMSE)	(RMSE)
		4.1				2.6			6.2			20.8			20.6
		$=\sqrt{\sum(a-c)^2}/n$	$=\sqrt{\sum(a-c)^2}$		$=\sqrt{\sum(a-c)^2}$	$=\sqrt{\sum(a-c)^2}/n$		$=\sqrt{\sum(a-c)^2}$	$=\sqrt{\sum(a-c)^2}/n$		$=\sqrt{\sum(a-c)^2}$	$=\sqrt{\sum(a-c)^2}/n$		$=\sqrt{\sum(a-c)^2}$	$=\sqrt{\sum(a-c)^2}/n$

Table 4.1b: Mamdani Fuzzy Model Evaluation Based On Defuzzification Techniques

Table 4.1a shows the samples of the four input variables and the predictions of the developed Fuzzy models. Gaussian Membership Function was used for all the models, their variations is in the defuzzification techniques. As shown, the output reveals a close similarity between Centroid, Bisector and the expected output. The next after the two is that of MOM, while LOM and SOM provide extreme value classifications. The extreme classifications from LOM and SOM are reflections of their names and operations. The LOM stands for Largest of the Maximum while SOM is the acronym for Smallest of the Maximum. It was on this premise that the average of the three best (Centroid, Bisector, MOM) was adopted as the expected output for the simulated data set. Mamdani Fuzzy with the Bisector Defuzzification techniques has the best precision. This as shown in the summary at the right-down side of table4.1a and as detailed in table4.1b. The second best is the Centroid, follow by the MOM, SOM and LOM respectively.

Having determined the best Mamdani Fuzzy Model for learner activities evaluation, the next set of experiments designed to evaluate the best Sugeno Fuzzy model was setup. The analysis is as shown in Table 4.2a. The results of SugenoFuzzy Models provide the basis for the Neuro-Fuzzy (ANFIS) model developed. The explanation of the performance of the untrained ANFIS, Backpropagation Trained and Hybrid Trained models are summarized in Table 4.2b.

Table 4.2a: Sugeno Fuzzy Model Evaluation Based On Aggregation and Defuzzification Techniques

S/N	Wtsum Defuzzification				Wtsum Defuzzification				Wtaver Defuzzification			
	Prob_Probor(a)	a-c	(a-c)^2	Prob_Probor(a)	a-c	(a-c)^2	Min_Max(a)	a-c	Min_Max(a)	a-c	(a-c)^2	
1	39.1	33.9	1147.4	47.0	26.0	677.0	44.3	28.8	826.7	117.0	44.0	1934.7
2	71.3	2.8	7.9	68.0	6.1	37.2	65.7	8.3	69.6	160.0	86.0	7388.0
3	39.5	31.8	1009.1	51.1	20.1	405.3	43.8	27.4	750.5	107.4	36.1	1305.7
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
147	91.8	75.7	5733.2	110.3	94.3	8890.6	89.6	73.5	5409.1	186.1	170.0	28906.2
148	32.3	0.8	0.6	38.1	6.6	44.0	37.3	5.8	33.6	138.8	107.3	11513.8
149	42.0	23.9	572.7	30.4	35.5	1262.7	43.9	22.1	489.1	76.2	10.2	103.8
150	35.0	19.7	386.2	9.6	5.8	33.3	46.4	31.1	965.6	47.3	32.0	1024.3
		4537.7	328565.6		5963.4	523408.8		4289.6	201406.6		13965.5	2090454.3
		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$
		(MAE)			(MAE)			(MAE)			(MAE)	
	30.3	2190.5		3489.4	28.6	1342.8		93.2	13936.4			
	$=\sum(a-c)/n$	$=\sum(a-c)^2/n$		$=\sum(a-c)/n$	$=\sum(a-c)/n$	$=\sum(a-c)^2/n$		$=\sum(a-c)/n$	$=\sum(a-c)^2/n$			
		(RMSE)		(RMSE)		(RMSE)		(RMSE)			(RMSE)	
		46.9		59.1		36.7		118.1				
		$=\sqrt{\sum(a-c)^2/n}$		$=\sqrt{\sum(a-c)^2/n}$		$=\sqrt{\sum(a-c)^2/n}$		$=\sqrt{\sum(a-c)^2/n}$				

Table 4.2b: Evaluation Training Methods in ANFIS

ANFIS(Prob_Probor/Wtaver)									
Before Training					After Backpropagation Training			After Hybrid Training	
Ref. No	Expected (c)	Before Training	a-c	(a-c)^2	Back propagation	a-c	(a-c)^2	Hybrid	a-c
1	73.0	39.1	33.9	1147.4	39.2	33.8	1145.3	70.2	2.8
2	74.1	71.3	2.8	7.9	71.0	3.1	9.4	70.0	4.1
3	71.2	39.5	31.8	1009.1	39.4	31.9	1014.8	63.6	7.7
:	:	:	:	:	:	:	:	:	:
147	16.0	91.8	75.7	5733.2	89.7	73.6	5423.7	33.3	17.2
148	31.5	32.3	0.8	0.6	32.3	0.8	0.7	32.7	1.2
149	66.0	42.0	23.9	572.7	42.1	23.9	570.2	57.5	8.4
150	15.3	35.0	19.7	386.2	35.0	19.6	385.9	31.5	16.2
			4537.7	328565.6		4469.5	311218.1		1329.0
			$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$
			(MAE)	(MAE)			(MAE)		(MAE)
			30.3	2190.5		29.8	2074.8		8.9
			$=(\sum(a-c))/n$	$=(\sum(a-c)^2)/n$		$=(\sum(a-c))/n$	$=(\sum(a-c)^2)/n$		$=(\sum(a-c))/n$
			(RMSE)	(RMSE)			(RMSE)		(RMSE)
				46.9			45.6		11.3
				$=\sqrt{(\sum(a-c)^2)/n}$			$=\sqrt{(\sum(a-c)^2)/n}$		$=\sqrt{(\sum(a-c)^2)/n}$

Table 4.2a shows the performance of four types of Sugeno Fuzzy Models. In all, the models with weight sum - Wtsum defuzzification are the best; they have the least MAE and RMSE values. Attempt was made to use the best model with Max-Min Aggregation and Wtsum defuzzification for Adaptive Neuro-Fuzzy Inference System (ANFIS) model development. However, it was realized that ANFIS does not support Sugeno with weight sum - Wtsum defuzzification, it supports only the Sugeno with weight average - Wtaver defuzzification. To this end, the Wtaver defuzzification model with the least value (59.1) was selected and made to be the bases for the ANFIS models whose performances are further shown in Table 4.2b. As shown, the table reveals the performance of three categories of the model. The first is the untrained model which is the direct transformation of the Sugenos. This untrained model was duplicated; the first copy was trained using the Back propagation method while the second copy was trained by the Hybrid (Least Square Estimation and Gradient Descent) method. The MAE and RMSE of the untrained ANFIS are 2190.5 and 46.9 respectively; this shows a very significant improvement over the Sugeno equivalent with MAE (3489.4) and RMSE (59.1). This improvement reveals the strength of the ANFIS architecture even before it is trained.

The quest for better model necessitates training of the formulated networks. The performance of the Back propagation trained model is 2074.8 for the MAE and 45.6 for the RMSE. These error figures are very high when compared with that of obtained when the Hybrid training methods were used. In the Hybrid model which is the best, the MAE was 127.4 and the RMSE was 11.3. This information establishes the fact that adaptive network trained by the Hybrid algorithm (Forward and Backward – two passes) outperform the untrained and a one pass trained network of the same architecture. This knowledge narrows the search to using Hybrid with the formulated membership function and the ANFIS model default

membership functions. The details of the experiment are as shown in the following Table4.3a and its continuation in Table4.3b.

Table 4.3a: Comparison of the Developed Method with Default ANFIS Models

Table 4.3a: Comparison of the Developed Method with Default ANFIS Models

Grid Partitioning										
Developed/Hybrid			Triangle/Hybrid			Gaussian/Hybrid				
Ref	Expte	Dev/	a-c	(a-c)^2	Triangle	a-c	(a-c)^2	Gaussian	a-c	(a-c)^2
1	73.0	70.2	2.8	7.6	57.6	15.4	236.9	56.8	16.2	261.4
2	74.1	70.0	4.1	16.8	68.5	5.5	30.7	64.9	9.2	85.1
3	71.2	63.6	7.7	58.9	71.1	0.1	0.0	69.0	2.2	4.8
.	.	.	.	.	.	.	.	.	.	.
14	16.0	33.3	17.2	296.6	38.0	21.9	480.6	.	22.9	525.3
14	31.5	32.7	1.2	1.5	39.9	8.5	71.7	39.0	6.6	42.9
14	66.0	57.5	8.4	71.1	43.8	22.2	491.6	38.0	19.3	374.1
15	15.3	31.5	16.2	261.6	19.2	3.8	14.7	46.6	2.3	5.3
			1329.0	19097.0		1507.2	24472.8	17.6	1457.6	24051.9
			$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$
			(MAE)				(MAE)			(MAE)
			8.9	127.4		10.1	163.2		9.8	160.4
			$=\sum(a-c)/n$	$=\sum(a-c)^2/n$		$=\sum(a-c)/n$	$=\sum(a-c)^2/n$		$=\sum(a-c)/n$	$=\sum(a-c)^2/n$
				(RMSE)			(RMSE)			(RMSE)
				11.3			12.8			12.7
				$=\sqrt{(\sum(a-c)^2)/n}$			$=\sqrt{(\sum(a-c)^2)/n}$			$=\sqrt{(\sum(a-c)^2)/n}$

Table 4.3b: Comparison of the Developed Method with Default ANFIS Models (continuation of Table 4.3a)

Grid Partitioning									
		G-Bells/ Hybrid		Sigmoid/ Hybrid					
Ref	Expecte	G-Bells/	a-c	(a-c)^2	Sigmoid	a-c	(a-c)^2		
1	73.0	56.2	16.8	283.3	60.5	12.5	156.5		
2	74.1	63.2	10.9	118.0	67.8	6.3	39.7		
3	71.2	67.8	3.5	12.2	69.5	1.7	3.0		
:	:	:	:	:	:	:	:		
14	16.0	40.7	24.7	609.8	39.0	23.0	527.2		
14	31.5	36.0	4.5	20.4	32.2	0.7	0.5		
14	66.0	46.6	19.3	374.4	44.0	22.0	484.1		
15	15.3	18.0	2.7	7.1	21.6	6.2	38.9		
			1458.6	25186.7		1391.9	23630.5		
			$=\sum(a-c)$	$=\sum(a-c)^2$		$=\sum(a-c)$	$=\sum(a-c)^2$		
			(MAE)				(MAE)	Precision Accuracy Measures	
								Models	RMSE
			9.8	168		9.3	157.6	Develope d	127.4
			$=(\sum(a-c)) / n$	$=(\sum(a-c)^2) / n$		$=(\sum(a-c)) / n$	$=(\sum(a-c)^2) / n$	Triangle	163.2
								Gaussian	160.4
				(RMSE)			(RMSE)	G. Bells	168.0
			13	13			12.6	Sigmoid	157.6
			$=\sqrt{(\sum(a-c)^2) / n}$	$=\sqrt{(\sum(a-c)^2) / n}$			$=\sqrt{(\sum(a-c)^2) / n}$		12.6

4.3c: Comparison of Neuro-Fuzzy Models Complexity

Model Types	Partitioning Methods	Optimization Techniques	Membership Functions	Training Time (sec)	Epoch	Training Errors	Training Data Errors	Validation Data Errors	Ranking
ANFIS I	Grid	Hybrid	Developed	5	40	10.6538	10.650	9.6042	1
			Radial Basis Function	5	40	12.5577	12.556	13.2108	3
			Gaussian	4	40	12.7555	12.752	13.3295	4
			G-Bells	5	40	13.2678	13.259	13.9856	5
			Sigmoid	5	40	12.7382	12.553	12.6077	2

2

The knowledge discovered in the results of the experiment on the best Sugeno fuzzy model in Table 4.2a and that of Table 4.2b on the appropriate choice of training algorithm came into play in designing equivalent ANFIS models. The models were developed by using four default membership functions (MF); the membership models considered are Triangular MF, Gaussian (MF), G-Bells MF and Sigmoid MF. The performances of these models were compared with the developed model that combined experts' knowledge with the training dataset. The MAE and RMSE for the developed model, the Triangular MF model and the Gaussian MF model are shown in table 4.3a. Table 4.3b has the performance values for the G-bells MF and Sigmoid MF models. The right-down corner of the same Table 4.3b has the summary of the models performances. The G-Bells model displays the worst performance, it was ranked 5th, because its performance estimates for the MAE and the RMSE are 168.0 and 13.0 respectively. The model with Triangular MF was ranked 4th, its MAE is 163.2 and its RMSE is 12.8. The 3rd in the ranking is the Gaussian MF based model. The table shows that the 2nd best model is the Sigmoid MF based model while best of the five models in consideration is the formulated model. The MAE and RMSE for the 2nd best are 157.6 and 12.6 respectively. The MAE and RMSE for the developed and best of the models are 127.4 and 11.3 respectively.

Furthermore, in Table 4.3c, the superiority of the developed model was further demonstrated. The developed model has the least complexity figures, followed by Sigmoid MF models. There is a swap of ranking position between the Triangle MF model and the Gaussian MF model. In complexity the Triangle MF model outperformed the Gaussian. The G-Bells model retained the worst performance ranking of 5th position.

4.2 Model Prediction Accuracy Measures

The choice of metrics selected for measuring a system's level of classification accuracy depends on the dataset distribution and the purpose of the measurement. Accuracy and Error Rate metrics are very good for balanced dataset. When a balanced dataset cannot be guaranteed then other metrics such as Precision, Recall and ROC analysis are preferable. In this work, metrics across the two categories are used for evaluating the developed model. These metrics as mentioned in section 4.1 are Accuracy, Precision and Recall. The measures of classification accuracy is as shown in Table 4.4a, the Confusion Matrix for the model is shown in Table 4.4b.

Table 4.4a: Measures of Classification Accuracy of the Models

Expected		Develop Model		Triangle Model		Gaussian Model		G-Bells Model		Sigmoid Model	
Positive		TP	67.0	TP	66.0	TP	67.0	TP	67.0	TP	64.0
		TN	74.0	TN	65.0	TN	66.0	TN	68.0	TN	67.0
		FP	9.0	FP	18.0	FP	17.0	FP	15.0	FP	16.0
	Total = 150.0	FN	0.0	FN	1.0	FN	0.0	FN	0.0	FN	3.0
Metrics											
		Accuracy	(TP +TN)	0.9	(TP +TN)	0.9	(TP +TN)	1.0	(TP +TN)	1.0	(TP +TN)
Precision		TP	/	0.9	TP	/	0.8	TP	/	0.8	TP
		TP	/	0.5	TP	/	0.5	TP	/	0.5	TP
Sample Classifications											
S/	Expected	Develop/Hybrid		Triangle/Hybrid		Gaussian/Hybrid		G-Bells/Hybrid		Sigmoid/Hybrid	
112	26.8	R	37.4	R	49.1	P	53.0	P	55.6	P	52.5
122	33.4	R	54.3	P	49.6	P	46.3	P	42.7	R	35.8
123	15.3	R	12.0	R	18.2	R	21.0	R	21.9	R	25.0
124	69.0	P	52.1	P	57.3	P	56.3	P	56.8	P	61.5
149	66.0	P	57.5	P	43.8	R	46.6	P	46.6	P	44.0

Table 4.4b: Confusion Matrix of the Models (remove s) Classification Accuracy

Expected	Develop Model		Triangle Model		Gaussian Model		G-Bells Model		Sigmoid Model	
Positive	TP	67.0	TP	66.0	TP	67.0	TP	67.0	TP	64.0
Negative	TN	74.0	TN	65.0	TN	66.0	TN	68.0	TN	67.0
Total = 150.0	FP	9.0	FP	18.0	FP	17.0	FP	15.0	FP	16.0
	FN	0.0	FN	1.0	FN	0.0	FN	0.0	FN	3.0
Metrics										
Accuracy		(TP +TN)	0.9	(TP +TN)	0.9	(TP +TN)	1.0	(TP +TN)	1.0	(TP +TN) 1.0
Precision										
Recall		TP /	0.9	TP /	0.8	TP /	0.8	TP /	0.8	TP / 0.8
Sample Classifications		TP /	0.5	TP /	0.5	TP /	0.5	TP /	0.5	TP / 0.5
S/	Expected	Develop/Hybrid		Triangle/Hybrid		Gaussian/Hybrid		G-Bells/Hybrid		Sigmoid/Hybrid
112	26.8	R	37.4	R	49.1	P	53.0	P	55.6	P 52.5
122	33.4	R	54.3	P	49.6	P	46.3	P	42.7	R 35.8
123	15.3	R	12.0	R	18.2	R	21.0	R	21.9	R 25.0
124	69.0	P	52.1	P	57.3	P	56.3	P	56.8	P 61.5
149	66.0	P	57.5	P	43.8	R	46.6	P	46.6	P 44.0

The analysis in Table 4.4a shows that Gaussian, G-Bells and Sigmoidal membership function based model have accuracy value of 1.0 which is higher by 0.1 when compared with the 0.9 of the developed and Triangle MF models. The less accuracy value of the developed model does not discredit its supremacy, this is because accuracy is a non sensitive metric especially when handling unbalanced dataset. Secondly and most importantly is the precision value in which the developed model has 0.9 where as the value for other models is 0.8. Finally, the developed model is at par with others in the Recall capability.

The Confusion Matrix as shown in Table 4.4b provides another evidence for rating the developed model higher than others. As indicated, the developed model has the best True Positive value of 67.0 which is the highest, though it shares this figure with Gaussian and G.Bell models. However, its strength over these two is vivid from its 9.0 False Positive (FP) value which is very low when compared with 17.0 and 15.0 for Gaussian and G.Bell models respectively. Furthermore, the developed model did not have a single False Negative and its True Negative (74.0) is the best. The implication of these figures among others is that the system will not in any way disadvantage the learners.

4.3 Analysis of Learners' Activities on CSCLAMS

The developed initiative of integrating Artificial Intelligent (AI) model into LMS was evaluated for its effectiveness. The metrics used include usability, acceptability and impacts.

The usability of the platform in this context is considered to be the functions of how it meets the essence for which it was setup. Table 4.5 summarizes the interactivities of the students on the platform.

Table 4.5: Summary of Students Interactivity Wednesday, 5 February 2014, 10:03 PM. to Sunday, 18 May 2014, 9:59 PM

Activity	Views	Related blog entries	Last access
News forum	151	-	Sunday, 18 May 2014, 9:59 PM (56 days)
<i>3 February - 9 February</i>			
csc 306 syllabus	106	-	Wednesday, 9 July 2014, 10:33 AM (4 days 11 hours)
Recommended Text 1	111	-	Wednesday, 4 June 2014, 4:20 PM (39 days 6 hours)
Recommended Text 2	58	-	Saturday, 3 May 2014, 5:54 PM (71 days 4 hours)
Participatory Course Planning	504	-	Sunday, 13 July 2014, 10:12 PM (16 mins 3 secs)
<i>10 February - 16 February</i>			
Introducing concept of System	600	-	Sunday, 13 July 2014, 10:11 PM (17 mins)
<i>17 February - 23 February</i>			
More on the fundamentals of system analysis and design	448	-	Sunday, 13 July 2014, 10:13 PM (15 mins 29 secs)
<i>24 February - 2 March</i>			
System Development Life Cycle (SDLC)	356	-	Monday, 26 May 2014, 2:30 PM (48 days 7 hours)

<i>3 March - 9 March</i>			
Csc 306 Survey 1	168	-	Wednesday, 9 July 2014, 10:28 AM (4 days 12 hours)
<i>17 March - 23 March</i>			
SDLC phases: Aims and Activities	310	-	Wednesday, 9 July 2014, 10:34 AM (4 days 11 hours)
<i>24 March - 30 March</i>			
UML for System Design	124	-	Friday, 2 May 2014, 8:00 PM (72 days 2 hours)
UML reading guide	391	-	Friday, 2 May 2014, 8:06 PM (72 days 2 hours)
<i>31 March - 6 April</i>			
Submit CSC 306 project proposal	3586	-	Wednesday, 9 July 2014, 10:39 AM (4 days 11 hours)
Analyse and Design your proposal	772	-	Thursday, 3 July 2014, 9:16 AM (10 days 13 hours)

The contents of Table 4.5 are auto-generated summaries of the students' interaction with the various resources throughout the duration of the course. Looking at the number of interactivities within the days and hours, it is evident that highest figures were recorded in the eight (8th) week – 31 March – 6 April. In the 8th week students were required to submit project proposals, thereby interacting with the Database activity type. The teacher assessed the proposals, make necessary observations that may require the students to review and re-submit as many times as necessary. On the other hand more hours that resulted into days could be noticed in all the weeks that have resources for the students to download. These instances are as in week 1- February 3 to February 9, where students need to download the recommended text 1 and text 2. Others are in week 4 - February 24 to March 2 where students need to download the material on System Development Life- Cycle (SDLC). Week 7 – March 24th to March 30 and week 8 – March 31st to April 6th, where students needed to download materials on UML for System Design and materials guiding students to good analysis and design of proposals respectively. Activity that attracts more interactivity after the discussed types is the survey in week 5. Details of the survey activities are summarized in Table 4.6.

Table 4.6: Survey Result on Platform Usability

	Submitted answers: 45 Questions: 11
1	Does the online platform increase your commitment to study CSC 306? - No: 11 (24.44 %) - Yes: 34 (75.56 %)
2	Does it increase your interactivity with your classmates? - No: 9 (20.00 %) - Yes: 36 (80.00 %)
3	Does it foster your quest to search for relevant course materials? - No: 0 - Yes: 45 (100.00 %)
4	How will you rate the course sequencing approach being used by the teacher? - Poor: 3 (6.67 %) - Fair: 18 (40.00 %) - Good: 24 (53.33 %)

	Good:
5	How will you rate your level of understanding of the Course so far? - Poor:  4 (8.89 %) - Fair: 25 (55.56 %) -  16 (35.56 %) Good:
6	Which of the following is/are your method(s) of Internet connectivity during your E-learning activities? Tick all that are applicable - The University Network:  36 (80.00 %) - Mobile ISP (Modems):  19 (42.22 %) - Internet Cafés:  17 (37.78 %)
7	Which of the following device(s) is/are readily available for your e-learning activities? Tick all that are applicable - Desktop:  8 (17.78 %) - Laptop: 42 (93.33 %)

	- Tablets: 3 (6.67 %) - Smart phone: 25 (55.56 %)
8	Would you like to take more courses online? - No: 21 (46.67 %) - Yes: 24 (53.33 %)

The survey, whose result is shown in Table 4.6, was conducted after a month into the implementation as an instrument for formative assessment. The intent was to elicit the perceptions of the students and to provide a feedback to the teacher, thereby providing bases for enhancement and adjustment were necessary. In all forty-five (45) students participated in the survey, their responses to eight (8) out of the eleven questions in the survey are shown in the table. The remaining three are open questions, samples of the students' responses to those questions are in Appendix C. The survey reveals that 75.56% of the respondents agreed that platform increases their commitments to the course. 80% of them submitted that the platform increases interactivity with classmates. All the respondents (100%) admitted that the platform fosters quest for searching relevant course materials. On the request to rate the course sequencing approaches being used by the teacher, 53.33% rated it as good and 40.00% as fair. Combination of the two Figures is 93.33% which is very okay, however the reasons for the remaining 6.67% that rated the sequence as poor are of concern. It was given an immediate attention because the poor rating was sustained in the question on students' level of understanding, while the percentage for the Good rating was surpassed by the Fair rating. Ordinarily, answers to question number 5 suppose to be a perfect reflection of that in question number 4. Question number 6 on Internet connectivity method(s) shows that 80.00% of students used the University Network (KWASUNET), follow by Mobile ISP Modems and lastly the Internet Cafes. This survey result divulges the gradual preference of Mobile ISP – Modem powered by mobile telecommunication networks over the café services for internet connectivity by users. The question on the type of computing devices used by the students allows an overlapping answers, this is because a particular student could use more than one type of devices overtime. In all 93.33% used Laptops, 55.56% used Smart phones, 17.78% used Desktops followed by 6.67% that used Tablets. In all

53.33% of the students are ready to take more courses online while 46.67% have some reservations. The reasons for the 46.67% saying 'NO' to the offer of more courses online are not unconnected to the current challenges of Electricity, Internet connectivity and the first timer syndrome. The students' reasons could be deduced from the collection of their raw comments in Appendix C.

4.4 Analysis of Learner's Academic Performance

Finally the overall impacts of this model on the academic performance of the students were measured. Descriptive statistics; the grade percentages and the class mean were used. The performance of students in CSC 306 in the 2011/2012, 2012/2013 sessions were compared with that of 2013/2014 in which the developed model was implemented. The summaries are as in Table 4.7 and shown in Figure 4.1.

Table 4.7: Raw Grades and Percentage (%) of Student’s Performances

	Raw and Percentage (%)) Grades of Students Performances						
	A	B	C	D	F	Total	Mean
2011/2012	4 (8.00)	6 (12.00)	6 (12.00)	6 (12.00)	28 (56.00)	50 (100.00)	37
2012/2013	3 (6.38)	11 (23.40)	18 (38.30)	9 (19.15)	6 (12.77)	47 (100.00)	53
2013/2014	6 (10.17)	17 (28.81)	22 (37.29)	12 (20.34)	2 (3.39)	59 (100.00)	56.98

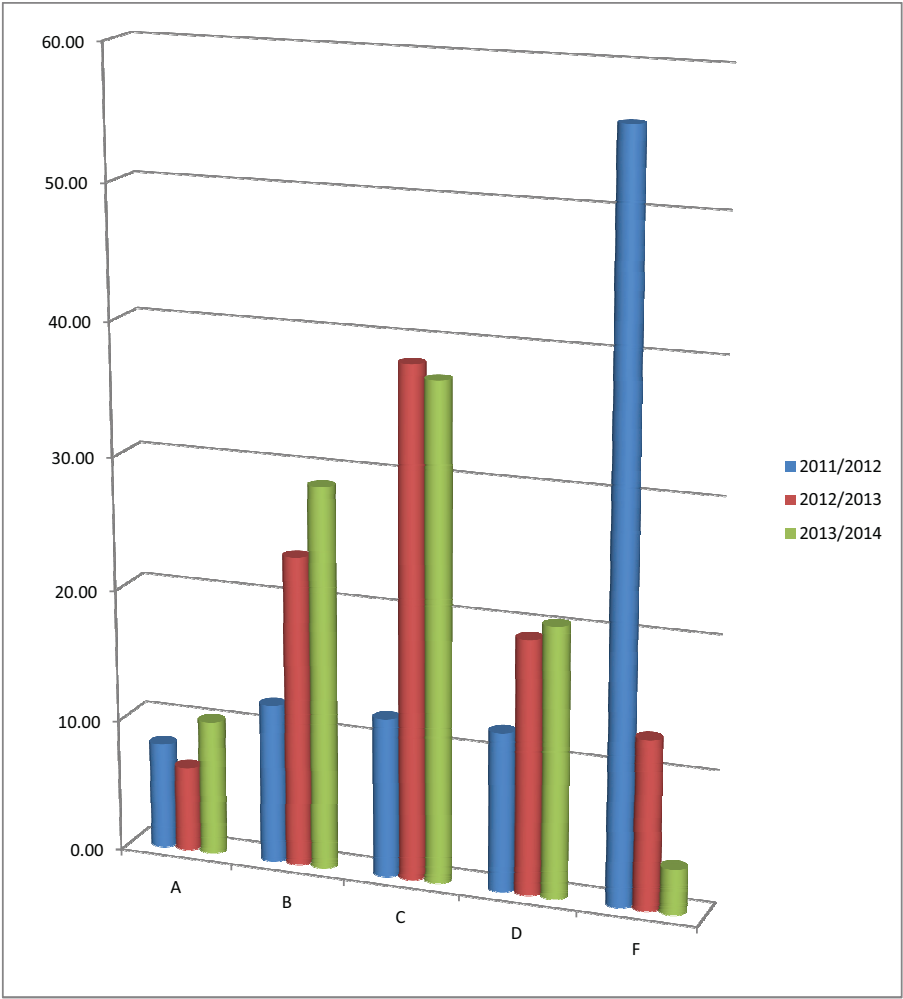


Figure 4.1: Graphs of Student’s Performances 2011/12, 2012/13, 2013/14

Table 4.7 shows the counts of the students by grades per session, the equivalent percentages are enclosed in brackets. The information in Figure 4.1 reveals that students' performances in 2013/2014 outperformed that of the two previous years. The mean value of the 2013/2014 set is 56.98, that of the 2012/2013 set is 53 and in 2011/2012, the class mean is 37. The percentage failure was 3.39% in 2013/2014, it was 12.77% in 2012/2013 and the worst case was 56% in 2011/2012.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the conclusion drawn from this research, the recommendations for the stakeholders in e-learning community and the contribution of this study to universal body of knowledge.

5.1 Conclusions

This study identifies considerable limitations of contemporary LMS to include weak support for instructional design theory- based lesson, provision of activity monitoring tools that are internal to the LMS and require teacher's attention for evaluation. With the former, the quality of courseware developed may not be guaranteed. This may prevent learning from taking place among the students. This situation will be disastrous because it will be difficult to track such situation for lack of physical and other forms of interactions that are limited in e-learning systems. Furthermore, the later problem would require the teacher's time and conscious efforts to interpret and take action. Additionally, the teacher's views are limited only to default statistics and graphs provided by the platform which may not meet his/her exact needs.

To ameliorate these challenges, in this project, a learners' activities auto evaluation model was formulated. The Neuro-fuzzy Artificial Intelligence model was integrated into the Learning Activity Delivery and Monitoring component. Furthermore, since evaluation is a function of comparing tracked values with a threshold, the Learning Design and Packaging component was also developed. This third component provides the teacher with dynamic platform for setting the required

threshold. The recommended principles in the IEEE LTSA and the ADL SCORM guide the designs.

The integrated model hosted at www.csclams.net was made available to the 300 level B.Sc Computer Science students of the Kwara State University in the Rain Semester of 2013/2014 academic session. Activities of these students in CSC 306 were monitored for the semester. The prediction accuracy and complexity of the developed model were very satisfactory. The result of the platform usability was very good and there was a noticeable improvement in students' academic performance. These results denote the essence of this initiative.

5.2 Recommendations

Continuous growth of e-learning users globally is a pointer to the fact that this research is very timely. While the current domain for the project would expectedly continue to be available, it is highly required that other courses be handled online via the platform. This will facilitate aggregation of students log traces that could be used for other types of behavioural, data mining and AI researches. Similarly, further works that could hinge on the methods and findings of this project should be encouraged. Such work could look into other areas that are out of the scope of this work. Some of these areas include contextual analysis of the students' logged information, study of the students behavioural pattern such as the early birds to respond to activities and how such behaviours impact their academic performance. Another important aspect of the work, is building an offline platform that could track offline behaviours and synchronize such with the server in subsequent connections. In the same vein, other Optimization techniques such as Least Square and Genetic Algorithm could be used instead of ANFIS to handle the transformation of Mamdani FIS to Sugeno FIS. Additionally, the developed models could be integrated into other Open Source LMS for performance

comparison. School proprietors and teachers should be properly educated on the potentials of e-learning system and on the need to commence earnest preparation for the inevitable changes. The preparation could be infrastructural, training and re-training of staff and content preparations. When these recommendations are implemented the E-learning community would have witnessed a tremendous progress over the current position.

5.3 Contributions to Knowledge

This research has contributed to knowledge in the following areas:

- i. The developed architecture provides a reference model for activity driven e-learning system with inbuilt quality assurance for instructional design.
- ii. The AI model provides a seamless evaluation of learners' activities that is devoid of human and other weaknesses associated with visualization techniques.
- iii. The study commenced construction of learners' activity dataset, which could be made available as public dataset for interested researchers worldwide, most especially those in educational data mining and AI.
- iv. The study establishes the effect of pedagogy on the quality of learner's activities and level of performance.
- v. The metrics identified in this study for tracking student's learning content exploration and depth of concentrations would provide an objective quality assurance in e-learning systems.

REFERENCES

Abraham, A. (2001): "Neuro Fuzzy Systems: State of Art Modelling Techniques". In proceedings of the sixth international work conference on Artificial and Natural Neural Networks, IWANN 2001, Granada, Springer Verlag Germany: 269-276.

ADL (2011): "SCORM 2004". Retrieved from <http://www.adlnet.gov/technologies/scorm> on 13-02-2012.

Afolabi, A.O., and Adagunodo, R. (2012): "Implementation of an Improved Facial Recognition Algorithm in a Web Based Learning System", International Journal of Engineering and Technology (IJET), 2(11): 1885-1892.

Ahmed, S.M. (2003): "The Implementation of Intelligent QOS Networking by the Development and Utilization of Novel Cross-Disciplinary Soft Computing Theories and Techniques". A Ph.D Dissertation, Department of computer science, The florida state university. Retrieved from <http://citeseerx.ist.psu.edu/viewdoc/download> on 28-09-2012.

Akinnuwesi, B.A., Uzoka, F.E., Olabiyisi, S.O., and Omodiora, E.O. (2012): "A Framework for User-centric Models for Evaluating the Performance of Distributed Software System Architecture". Expert Systems with Applications, 39:9323-9339.

Alexandros, P. and Susanne L. (2004): "Adaptive Learning Environments and E-learning Standards". Electronic Journal on E-learning, 2 (1): 181-194.

Al-Hmouz, A. , Shen, J., Al-Hmouz,A. and Yan, J. (2012): " Modeling and Simulation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Mobile Learning", IEEE Transactions on Learning Technologies, 5(3): 226-236.

Anderson, K., and Either, J. (2004): "Cooperative Education for All Students: Rethinking the Critical Learning and Educational Outcomes". Annual Conference of the Cooperative Education and Internship Association. Arlington, VA.

Arnold, K.E. (2010): "Signals: Applying academic analysis," EDUCAUSE Quarterly 33(1). Retrieved from <http://er.educause.edu/articles/2010/3/signals-applying-academic-analytics> on 24-09-2012

Asteriadis, A., Tzouveli, T., Karpouzia, K., and Kollias, S. (2008: "Estimation of Behavioural User State Based on Eye Gaze and Head Pose - Application in an E-learning Environment". Springer Science.

Babu S. C. (2001): "E-learning Standards". In the Proceedings of the ELELTECH India National Seminar on E-learning & E-learning Technologies. Retrieved from www.cdacindia.com on 11-08-2011.

Babuska, R. (2001): "Fuzzy systems, modeling and identification," Technical report, Delft University of Technology, Netherland.

Baker, R.S.and de Carvalho A.M.(2008): “labeling student behaviour faster and more precisely with text replays”. Proceedings of 1st international Conference on Educational Data Mining: 38-47.

Binglan, H. (2001): "Student modelling and adaptivity in web based learning system". Retrieved from <http://citeseerx.ist.psu.edu/viewdoc/download> on 30-09-2012.

Blanco, A., Serano, A., Freire, M., Mentinez, I., and Fremandez, B. (2013): “E-learning Standards and Learning Analytics: Can Data Collection Be Improved by Using Standard Data Model?”, 2013 IEEE Global Engineering Education Conference (EDUCON), Berlin – Germany: 1255-1261.

Bonk, C., and King, K. (1998): "Computer conferencing and collaborative writing tools: Starting dialogue about student dialogue". Electronic Collaborators: 3-23.

Borsook, T., (1991): “Harnessing the Power of Interactivity for Instruction”, Proceedings of the 1991 Convention of the Association for Educational Communications and Technology: 103-117.

Branson, R., Rayner, G., Cox, G., Furman, J.L., King, J.P., and Hannum, F. (1975): "Interservice procedures for instructional system development". Ft. Monroe, VA: U.S: Army Training and Doctrine Command.

Brusilovsky, P. (1996): "Methods and techniques of adaptive hypermedia". User Modelling and User-Adapted Interaction, 6: 87-129.

Brusilovsky, P. (2003): "Developing Adaptive Education Hypermedia Systems: From Design Models to Authoring Tools", in Murray, T., Blessing S., and Ainsworth, S. (eds.), Authoring Tools for Advanced Learning Technologies, Kluwer Academic Publishers, NL.

Brusilovsky, P., and Peylo, C. (2003): "Adaptive and Intelligent Web- based educational systems". International Journal of Artificial Intelligence in Education,13: 156-169.

Brusilovsky, P.L. (1994): "The construction and application of student models in intelligent tutoring systems". Journal of Computer and Systems Sciences International, 32(10): 70-89.

Bunt, A.and Conati, C.(2004): "Probabilistic Student Modelling to Improve Exploratory Behaviour". Department of Computer Science, University of british Columbia, Vancouver, BC, V6T1Z4, Canada.

Carlsor, R.D., and Rapman, J. (2009): "Web-based Interactivity", WebNet Journal, 1(2): 11- 13.

CED (2009): "Harnessing Openness to Improve Research, Teaching and Learning in Higher Education". A Publication of the Committee for Economic Development Digital Connection Council. ISBN. #0-87186-184-7. Retrieved from <http://www.ced.org>, on 22-06-2011.

Ceddia, J., Sheard, J., and Tibbey, G. (2007): "WAT- A Tool for Classifying Learning Activities from a Log File". Ninth Australasian Computing Education Conference (ACE 2007). Ballarat, Victoria, Australia.

Chayanukro, S., Mahmuddin, M., and Husni, H (2012): "Behaviour Usage Model to Manage the Best Practice of E-learning". Knowledge Management International Conference (KMICe) July 4-6 2012, Johor Bahru, Malaysia: 87-92

Churchill, D. (2007): "Towards a useful classification of learning objects". Educational Technology Research and development, 55 (5).

Conati, C., Gertner, A. and Vanlehn, K. (2002): "Using Bayesian networks to manage uncertainty in student modelling". User Modelling and User-Adapted Interaction: 371–417.

Conole, G., and Fill, K. (2005): "A Learning design toolkit to create pedagogically effective learning activities". Journal of Interactive Media in Education .

Corbiere, A. and Choquet, C. (2002): "Designer Integration In Training Cycles: IEEE LTSA Model Adaptation", Retrieved from <http://www-ic2.univ-lemans.fr/lium> on 09/01/2013

Dai, S., and Zhang, P. (2008): "A Data Mining Algorithm in Distance Learning". Paper presented at the CSCWD 2008. 12th International Conference on Computer Supported Cooperative Work in Design.

Dewey, J. (1938): "Experience and Education". New York: Macmillan

Dick, W., and Carey, L. (1996): "The systematic design of instruction". (4th, Ed.) New York: Harper Collin.

DOD. (2001): "Development of interactive multimedia". USA, Department Of Defence.

Esichaikul, V., Lamnoi, S., and Bechter, C. (2011): "Student Modelling in Adaptive E-learning Systems. Knowledge Management & E-learning" An International Journal, 3(3): 343-355.

Felder, R.M. and Solomon, B.A. (1997): "Index of learning Styles questionnaire". Retrieved from <http://www.engr.ncsu.edu/learningstyles/ilsweb.html> on 12/10/2013

Florian, B., Glahn, B., Drachsler, C., Specht, H. M., and Fabregat, R. (2011): "Activity-based learner-models for learner monitoring and recommendations in moodle," Towards Ubiquitous Learning: Lecture Notes in Computer Science. 6964: 111-124.

Friesen, N.(2004): "A gentle Introduction to Technical E-learning Standards". A Canadian Journal of Learning and Technology. 30 (3)

Gagne, R. (1988): "Essentials of learning for instruction". Englewood Cliffs, NJ: Prentice Hall.

George, J.K. and Bo, Y (1995): "Fuzzy Sets and Fuzzy Logic: Theory and Applications". Prentice Hall, New Jersey 07458

Godjevac, J. (1993): "State of the Art in the Neuro Fuzzy Field". Technical Report 93.25

Govaerts, S., Duval, E., Verbert, K., and Pardo, A., (2012): "The Student Activity Meter for Awareness and Self Reflection", ACM, Austin-Texas, USA

Greer, J.E. and McCalla, G.I.(Eds), (1994): "Proceedings of NATO Advanced Research Workshop on Students Modelling: The Key to Individualized Knowledge-Based Instruction", Ste. Adele, Que., Canada, May 4-8, 1991, NATO ASI Series, F125, Springer-Verlag, Berlin.

Hagan, M.T. and Demuth, H.B. (1996): "Neural Network Design", USA, PWS Publishing Company.

Hannafin, M., Hannafin, K., S.M.Land, and Oliver, K. (1997): "Grounded practice and the design of learning systems". Educational Technology Research and Development, 45 (3): 101-117.

Hijon, R., and Carlos, R. (2006): "E-learning platforms analysis and development of students tracking functionality". In Proceedings of the 18th World Conference on Educational Multimedia, Hypermedia & Telecommunications: 2823-2828.

Hirumi, A. (2002): "The design and sequencing of E-learning interactions: a grounded

approach". International journal on E-learning, USA, Retrieved from <http://www.thefreelibrary.com> on 09/03/2013.

Hogo, M.A. (2010): "Evaluation of E-Learnings Behaviour using Different Fuzzy Clustering Models: A Comparative Study", International Journal of Computer Science and Information Security, 7(2): 131-139, Retrieved from <http://sites.google.com/site/ijcsis> on 06/06/2013.

Hyunjong, C., and Taeyoung, K. (2005): "An Enhanced LTSA Model Providing Contextual Knowledge for Intelligent E-Learning Systems", Journal of Information Science and Engineering, 21: 849-858.

IEEE. (2001): "IEEE Learning Standards Technology Committee (LSTC)". Retrieved from <http://lstc.ieee.org> on 23/04/2010

IEEE. (2004): "IEEE standard for learning technology (2004). Data Model for Content Object Communication". IEEE Std 1484.11.

ISO, (2004): "The magical demystifying tour of ISO 9000 and ISO 14000- In the beginning". Retrieved from <http://www.iso.org> on 23/04/2010

Jang, J.R., Sun , C.T., and Mizutani, E. (1997): "Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence". USA: Prentice-Hall,Inc.

Jason, C., Judy, S. and Grant, T. (2007): "WAT- a tool for classifying learning activities from a log file", 9th Australasian Computing Education Conference, Ballarat, Victoria, Australia.

Jones, M.T. (2008): "Artificial Intelligence: A Systems Approach". Infinity Science Press LLC, New Delhi

José, V., Fernando, M.D. and Alexandre, M.,(2004): "Neuro-Fuzzy Systems: A Survey", WSEAS Transactions on Systems, 3(20): 414-419.

Karagiannidis, C., Sampson, D., and Cardinali, F. (2001). "Integrating Adaptive Educational Content into Different Courses and Curricula". Educational Technology & Society, (4) 3.

Karampiperis, P. and Sampson, D. (2005): "Towards Next Generation Activity-based Learning Systems". 5th IEEE International Conference on advanced Learning Technologies, Kaohsiung, Taiwan.

Kashihara, A., Kinshuk, Oppermann, R., Rashew, R., and Simm, H. (2000): Journal of education multimedia and hypermedia, 9(3): 253-276.

Kinshuk, A., Nikov, A. and Patel, A. (2001): "Adaptive Tutoring in Business Education Using Fuzzy Back Propagation Approach". In Proceedings of the Ninth International Conference on Human-Computer Interaction: 465-468.

Kolb, D.A (1984): "Experiential Learning: Experience as the Source of Learning and Development". Englewood Cliffs, NJ: Prentice Hall. Retrieved from

<http://www.learningfromexperience.com/images/uploads/process-of-experiential-learning.pdf> on 19/04/2010

Kuljis, J. and Liu, F., (2005): "A comparison of learning style theories on the suitability for elearning". Proceedings of the IASTED Conference on Web Technologies, Applications, and Services. ACTA press: 191-197.

Li, X. and Chang, S. (2005): "A Personalized E-learning System Based on User Profile Contracted Using Information Fusion". DMS'05, pp. 109-114. Banff, Canada.

Lin, C., Chen, K., and Tsai, C. (2008): "Modeling the Examinee Ability on the Computerized Adaptive Testing Using Adaptive Network-Based Fuzzy Inference System", in Proceedings of IEEE Asia-Pacific Services Computing Conference: 139-144.

LSTA. (2001): "IEEE Learning Systems Technology Architecture". Retrieved from <http://lsta.ieee.org> on 23/04/2010

Marian , B.G. (2002): "Computational Intelligence Systems and Applications". Springer Verlag.

May, M., George, S., and Prevot, P. (2007): "Analysing, and visualisizing learner's activities on discussion forum," IASTED International Conference on Web-based Education (WBE 2007), Chamonix, France: 649-656

May, M. and George, S. (2011): "Using learning tracking data to support student's self monitoring". 3rd International Conference on Computer Supported Education, France: 46-55,

MathWorks (1999): "Fuzzy Logic Toolbox User's Guide 1995 – 1999", The MathWorks, Inc.

McMullen, D. (2011): "A Framework for the Assembly and Delivery of Multimodal Graphics in E-learning Environment". Ph.D Dissertation, Dublin City University. Dublin.

Merrill, M., Drake, L., Lacy, M., and Pratt, J. (1996): "Reclaiming Instructional design. Educational Technology". 36 (5): 5-7.

Moore, M. (1989): "Editorial: three types of interaction". The American Journal of Distance Education , 3 (2): 1-6.

Nauck, D., Klawon F. and Kursse R. (1997): "Foundations of Neuro-Fuzzy Systems". J. Wiley & Sons

Nikam, S.R., Nikumbh P.J., and Kulkarni, S.P (2012): "Fuzzy Logic And Neuro-Fuzzy Modelling". Recent Trends in Computing. International Journal of Computer Applications (IJCA)ISSN: 0975 – 8887, 22: 22-31.

Nor Azan, M.Z. and Wong, S.Y.(2007): "Learning activities management system," Proceedings of International Conference on Electrical Engineering and Informatics, Institut Teknologi Bandung, Indonesia: 488-491.

Northrup, P. (2001): "A framework for designing interactivity in Web-based instruction". Educational Technology , 41 (2): 31-39.

Perry, J.D.(2001): "Learning and Cognition". Retrieved from <http://education.indiana.edu/~p540/webcouse/gagne.html> on 23/05/2011

Ramjeet, S.Y., and Vijendra, P.S. (2011): "Modeling Academic Performance Evaluation Using Soft Computing Techniques: A Fuzzy Logic Approach", International Journal on Computer Science and Engineering, 3(2): 676 – 686.

Reiser, R.A. & Dempsey, J.V. (2007). "Trends and Issues in Instructional Design", 2nd ed., Upper Saddle River, NJ: Pearson Education, Inc.

Recker, M., and Wiley, D. (2001): "A Non-authoritative Educational Metadata Ontology for Filtering and Recommending Learning Objects". Interactive Learning Environments , 9 (3): 23-27.

Reiser, R., and Dempsey, J. (2012): "Trends and issues in instructional technology". Boston: Pearson Education, Inc.

Robert, T., and Timothy, J. (2009): " Extending SCORM LOM". Issues in Informing Science and Information technology, 6: 863-875.

Sabbir, A.K. (2004): "A Conceptual Framework for Web-based Intelligent Learning Environments using SCORM-2004". Proceedings of the IEEE International Conference on Advanced Learning Technologies (ICAL' 04).

Kumar, P., Samaddar, S.G., Samaddar, A.B., and Misra, A.K. (2010): "Extending IEEE LTSA E-Learning Framework in Secured SOA Environment", Proceedings of 2nd International Conference of Education technology and Computer (ICETC), IEEE: 136-140.

Sadique, A. Ashok A.G. (2005): "An Adaptive Neuro Fuzzy Inference System For Student Modelling In Web- Based Intelligent Tutoring Systems". International Journal on E-learning, 1(1): 19 –27.

Scarpiniti, M. (2009): "Fuzzy Logic-Lesson 9". Retrieved from <http://ispacading.uniroma1.it/scarpiniti/index.htm> on 21/04/2011

Self, J. (1990): " Bypassing the Intractable Problem of Student Modelling". AAI/AI-ED Technical Report No. 41 in Frasson, C. and Gauthier, G. (eds), Intelligent Tutoring Systems: at the Crossroads of Artificial Intelligence and Education, 107-23, Norwood, N.J.: Ablex. <http://www.lans.ac.uk/computing/research/aai-aied>.

Self, J.(1994): "Formal Approaches to Students Modelling". AAI/AI-ED Technical Report No. 92 in Greer, J.E. and McCalla, G.I.(Eds), Students Modelling: The Key to Individualized Knowledge-Based Instruction, Berlin: Springer-Verlag :295-351

Sengupta, S., Chaki, N., and Dangupta, R. (2009): "Learner's Quanta Based Design of a Learning Management System", International Journal of Education and Information Technologies, 1(3): 67-74.

Sevarac, Z. (2006): "Neuro fuzzy reasoner for student modelling". In Advanced Learning Technologies, 2006. IEEE Sixth International Conference : 740-744.

Shale, D., and Garrison, D. R. (1990): " Education and communication", In O. R. Garrison and D. Shale (Eds.). Education at a distance, Malabar, FL: Robert E. Krieger Publishing: 23-39,

Shute, V. and Towle, B. (2003): "Adaptive E-learning". Educational Psychologist, 38(2): 105-114

Siegele, L. (2003). "Survey: The IT Industry. The Economist". Retrieved from http://www.economist.com/surveys/displayStory.cfm?Story_id=1747362 on 23/04/2012

Stathacopoulou, R., Magoulos, G.D. and Grigoriadou, M. (1999): "Neural network-based fuzzy modelling of the student in intelligent tutoring systems". In International joint Conference on Neural Networks, 1999. 5: 3517-3521.

Stathacopoulou, R., Magoulos, G.D., Grigoriadou, M., and Samarakau, M. (2004): "Neuro-fuzzy Knowledge Processing in Intelligent Learning Environments for Improved Student Diagnosis". Elsevier Inc.

Stracke, C.M. (2010): "Categories and Purposes of (E-learning) Standards: The Need for Harmonization of Interoperability and Quality Development"; Position Paper for the JISC/CETIS Future of Interoperability Standards Meeting 2010 in Manchester, UK. Retrieved from <http://www.qed-info.de/downloads> on 3/04/2010.

Sun, Z., and Finnie, G. (2004): "Intelligent Techniques in E-Commerce: A Case-based \ reasoning Perspective". Heidelberg: Springer-Verlag.

Sun, Z., and Finnie, G. (2005): "Experience management in knowledge management". Information Technology papers. Paper 103. Retrieved from http://epublications.bond.edu.au/infotech_pubs/103 on 23/04/2010.

TechLearn, (2001): "SCORM Concept". Retrieved from <http://www/eduworks.com>

Tzouveli, P., Mylonas, P., and Kollias, S. (2008): "An intelligent E-learning system based on learner profiling and learning resources adaptation". Computer Education 51(1): 224–238.

VanLehn, K. (1998): "Evaluation of an assessment system based on Bayesian student modelling". International Journal of Artificial Intelligence in Education, 8(2).

Verlami, I., and Apostolakis, I. (2006): "The Present and Future of Standards for E-learning Technologies". Interdisciplinary Journal of Knowledge and Learning Objects, 2: 59-76.

Vladan, D., Jelena, J., and Dragan, G. (2007): "The Pragmatics of Current E-learning Standards". IEEE Internet Computing: 16-24.

Voss. A., (1996): "Towards a Methodology For Case Adaptation". In. Wahlster W. (ed): Proceedings 12th European Conference on Artificial Intelligence (ECAI'96), John Wiley and Sons.

Wenger, E. (1987): "Artificial Intelligence and Tutoring Systems: Computational and Cognitive Approaches to the Communication of knowledge", Morgan Kaufmann Publishers, Inc.

Wiley, D. (2002): "The Instructional use of learning objects". Retrieved from <http://reusability.org/read/> on 13/02/2010

Winterstein, T. (2007): "402 Getting Started with eLearning Standards and SCORM".: HunterStone, USA. Inc. Retrieved from <http://www.HunterStone.com> on 23/04/2010

Xiaofei, L., Abdulmotaleb, E., and Nicolas, D. (2003). "An Implementable Architecture of An E- Learning System". Proceeding of the Canadian Conference on Electrical and Computer Engineering (CCECE 2003): 1-4.

Yager, R.R. and Filev, D.P.(1994): "A Simple Adaptive Defuzzification Method", IEEE Transactions on Fuzzy Systems, 1(1): 69-78.

Yashpal, S. and Alok, S.C (2009): "Neural Networks in Data Mining", Journal of Theoretical and Applied Information Technology: 37-40.

Yildiz, O., Bal, O., and Gulsecen, S.(2013): "Improved Fuzzy Modelling to Predict the Academic Performance of Distance Education Students". The

International Review of Research in Open and Distance Learning, 2013, 14(5): 144-164

Zadeh, L. A. (1965): "Fuzzy sets", Information and Control 8: 338-353.

Zadeh, L.A.(1999): "Outline of a new approach to the analysis of complex systems and decision processes". IEEE Trans. on systems, Man and Cybernetics, 3 (1): 28-44.

Zatarin, C.R., Barron, M.L., Camacho, L.O., and Reyes, C.A. (2013): "Integrating Learning Styles and Affect with an Intelligent Tutoring System", Proceedings of 12th Mexican International Conference on Artificial Intelligence (MICAI), Mexico, IEEE: 247-253.

Appendix A: Sample PhP and Ajax Codes/ Matlab Codes

Part I: Sample PhP and Ajax Codes

```
<?php
@session_start();
@require_once "connect.php";
@require_once "function.php";
$id=$_REQUEST['option']; //id determines the section of ajax script to run

if($id=='login')
{
//login section
$username=@$_REQUEST['uname'];
$password=@$_REQUEST['pass'];
$role=@$_REQUEST['role'];

$res_l=@mysql_query("select * from roletb where username='$username' and
password='$password' and role='$role'");
if(@mysql_num_rows($res_l)>=1)
{
$rs_l=@mysql_fetch_array($res_l);
$_SESSION['login_id'] = $username;
$_SESSION['login_role'] = $role;
echo "<script> location='main.php';</script>";
} //record found
else
```

```

{
echo "<font color='red'><strong>Invalid login parameters</strong></font>";
} //record not found
}

if($id=='save_ped')
{
$pedid=$_REQUEST['pedid'];
$pedname=$_REQUEST['pedname'];
$pedmaxstep=$_REQUEST['pedmaxstep'];
$res_ped=mysql_query("select * from pedagogytb where pedid='$pedid'");
if(mysql_num_rows($res_ped)>=1)
{
echo "Pedagogy exist";
}
else
{
mysql_query("insert          into          pedagogytb          set
pedid='$pedid',pedname='$pedname',pedmaxstep='$pedmaxstep'");
echo "Saved successfully";
}
}

if($id=='next_id')
{

```

```

$pedid="PED".(get_next_ped_id() + 1);
echo "<input name='pedid' type='text' id='pedid' value='$pedid' />";
}

if($id=='view_all_ped' or $id=='delete_ped')
{
if($id=='delete_ped')
{
$rec_id=$_REQUEST['rec_id'];
mysql_query("delete from pedagogytb where id='$rec_id'");
}

$res_ped=mysql_query("select * from pedagogytb order by pedid");
$sn=0;
$tb="<table      border='1'      bordercolor='blue'><tr><th>S/N</th><th>PED
ID</th><th>PED NAME</th><th>PED MAXSTEP</th><th>ACTION</th></tr>";
while($rs_ped=mysql_fetch_array($res_ped))
{
++$sn;
$id=$rs_ped['id'];
$pedid=$rs_ped['pedid'];
$pedname=$rs_ped['pedname'];
$pedmaxstep=$rs_ped['pedmaxstep'];
$tb.="<tr><td>$sn</td><td>$pedid</td><td>$pedname</td><td>$pedmaxstep
</td><td><a onclick=\"multi_fx('delete_ped','$id')\">DELETE</a></td></tr>";

```

```
} //end of while
```

```
$tb.="</table>";
```

```
echo $tb;
```

```
}
```

```
if($id=='search_ped')
```

```
{
```

```
$pedid=$_REQUEST['pedid'];
```

```
$res_ped=mysql_query("select * from pedagogytb where pedid='$pedid'");
```

```
$rs_ped=mysql_fetch_array($res_ped);
```

```
$pedname=$rs_ped['pedname'];
```

```
$pedmaxstep=$rs_ped['pedmaxstep'];
```

```
$j=array(
```

```
pedname=>$pedname,
```

```
pedmaxstep=>$pedmaxstep
```

```
);
```

```
$j=json_encode($j);
```

```
echo $j;
```

```
}
```

```
//<!-- Pedagogystep section -->
```

```
if($id=='next_step')
```

```

{
$pedid=$_REQUEST['pedid'];
$pedstep=$pedid."_".(get_next_ped_step($pedid) + 1);
echo "<input name='step' type='text' id='step' value='$pedstep' />";
//echo "<input name='step' type='text' id='step' value='$pedstep' /> ";
}

if($id=='save_pedstep')
{
$pedid=$_REQUEST['pedid'];
$pedstep=$_REQUEST['step'];
$peddesc=$_REQUEST['stepdescription'];
$res_pedstep=mysql_query("select * from pedsteptb where pedid='$pedid'
AND step='$pedstep'");
if(mysql_num_rows($res_pedstep)>=1)
{
echo "Pedagogy exist"; exit;
}
else
{
mysql_query("insert          into          pedsteptb          set
pedid='$pedid',step='$pedstep',stepdescription='$peddesc'");
echo "Saved successfully";
}
}

```

```

if($id=='search_pedstep')
{
$pedid=$_REQUEST['pedid'];
$pedstep=$_REQUEST['step'];
$peddesc=$_REQUEST['stepdescription'];
$res_pedstep=mysql_query("select * from pedsteptb where pedid='$pedid'");
$rs_pedstep=mysql_fetch_array($res_pedstep);
$stepdesc=$rs_pedstep['stepdescription'];
$j=array(
stepdescription=>$stepdesc
);
$j=json_encode($j);
echo $j;
} // The Codes Continues. This is just for Pedagogy and Pedagogy Steps

?>

```

Part II: Sample Matlab Codes

```
function varargout = evaluationpanel(varargin)
% EVALUATIONPANEL M-file for evaluationpanel.fig
%
%       EVALUATIONPANEL, by itself, creates a new
EVALUATIONPANEL or raises the existing
%       singleton*.
%
%       H = EVALUATIONPANEL returns the handle to a new
EVALUATIONPANEL or the handle to
%       the existing singleton*.
%
%
EVALUATIONPANEL('CALLBACK',hObject,eventData,handles,...
.) calls the local
%       function named CALLBACK in EVALUATIONPANEL.M
with the given input arguments.
%
%       EVALUATIONPANEL('Property','Value',...) creates
a new EVALUATIONPANEL or raises the
%       existing singleton*. Starting from the left,
property value pairs are
%
%       applied to the GUI before
evaluationpanel_OpeningFcn gets called. An
%       unrecognized property name or invalid value
makes property application
%
%       stop. All inputs are passed to
evaluationpanel_OpeningFcn via varargin.
```

```

%
%      *See GUI Options on GUIDE's Tools menu.  Choose
"GUI allows only one
%      instance to run (singleton)".
%
% See also: GUIDE, GUIDATA, GUIHANDLES

% Edit the above text to modify the response to help
evaluationpanel

% Last Modified by GUIDE v2.5 19-Aug-2014 22:53:47

% Begin initialization code - DO NOT EDIT
gui_Singleton = 1;
gui_State = struct('gui_Name',       mfilename, ...
'gui_Singleton',  gui_Singleton, ...
'gui_OpeningFcn', @evaluationpanel_OpeningFcn, ...
'gui_OutputFcn',  @evaluationpanel_OutputFcn, ...
'gui_LayoutFcn',  [] , ...
'gui_Callback',   []);
if nargin && ischar(varargin{1})
gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
[varargout{1:nargout}] =     gui_mainfcn(gui_State,
varargin{:});

```

```

else
gui_mainfcn(gui_State, varargin{:});
end
% End initialization code - DO NOT EDIT

% --- Executes just before evaluationpanel is made
visible.
function evaluationpanel_OpeningFcn(hObject, eventdata,
handles, varargin)
% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a future
version of MATLAB
% handles     structure with handles and user data (see
GUIDATA)
% varargin    command line arguments to evaluationpanel
(see VARARGIN)

% Choose default command line output for
evaluationpanel
handles.output = hObject;

% Update handles structure
guidata(hObject, handles);
% UIWAIT makes evaluationpanel wait for user response
(see UIRESUME)
% uiwait(handles.figure1);

```

```

conn = database('matlabconn','roots','');

% --- Outputs from this function are returned to the
command line.
function varargout = evaluationpanel_OutputFcn(hObject,
eventdata, handles)
% varargout    cell array for returning output args (see
VARARGOUT);
% hObject      handle to figure
% eventdata    reserved - to be defined in a future
version of MATLAB
% handles      structure with handles and user data (see
GUIDATA)
% Get default command line output from handles
structure
varargout{1} = handles.output;
% --- Executes on button press in evaluationbtn.
function evaluationbtn_Callback(hObject, eventdata,
handles)
% hObject      handle to evaluationbtn (see GCBO)
% eventdata    reserved - to be defined in a future
version of MATLAB
% handles      structure with handles and user data (see
GUIDATA)
global MYCHOICE,
if strcmp( MYCHOICE, 'one')
msgbox('single id','NF Learner Evaluation');

```

```

logintimeout(5);
conn = database('matlabconn','root','');
if isconnection(conn)

setdbprefs('DataReturnFormat','numeric');
cur = exec(conn, 'select * from temp_input');
cur = fetch(cur);
tempinput = cur.data;
%if isempty(handles.studentid)
% load testingdataset.dat;
%load tempinput;
fismat = readfis('e_learningusers');
r = evalfis(tempinput, fismat);

% Build temp_output_disp
exec(conn,'DELETE from temp_output_disp');
colnames = {'studentid','classvalue', 'remarks'};
cur = exec(conn, 'select * from temp_input_disp');
cur = fetch(cur);
exdata(1,1)={cur.data(1,1)};
exdata(1,2)={r};
if r>50
exdata(1,3)={'Pass'};
else
exdata(1,3)={'Fail'};
end

```

```

fastinsert(conn,'temp_output_disp',colnames,exdata);

% Display temp_output_disp
setdbprefs ('DataReturnFormat','cellarray');
cur = exec(conn, 'select * from temp_output_disp');
cur = fetch(cur);
set(handles.outputtb,'Data',cur.data);
end
else
if strcmp(MYCHOICE,'two')
msgbox('class list','NF Learner Evaluation');
load testingdataset.dat;
fismat = readfis('e_learningusers');
r = evalfis(testingdataset, fismat);
%set(handles.outputtb,'Data',r);           %for now
r = 'classevaldataset1.dat';
r = importdata(r);
set(handles.outputtb,'Data',r);
end
end

function studentid_Callback(hObject, eventdata, handles)
% hObject    handle to studentid (see GCBO)
% eventdata  reserved - to be defined in a future
version of MATLAB

```

```

% handles      structure with handles and user data (see
GUIDATA)

% Hints:  get(hObject,'String')  returns  contents  of
studentid as text
%          str2double(get(hObject,'String'))  returns
contents of studentid as a double
global MYCHOICE;
MYCHOICE = 'one';
chkid = get(handles.studentid, 'string');
if ~isempty(chkid) %chk aggregatetb for id, then
logintimeout(5);
conn = database('matlabconn','root','');
if isconnection(conn)

setdbprefs('DataReturnFormat','numeric');
%cur = fetch(conn, 'select ncomplete,ntime, nsubmit,
nquiz from learning_activities where studentid = 123');
%cur = exec(conn, ['select ncomplete,ntime, nsubmit,
nquiz from learning_activities where studentid =' ''''
chkid '''']);
cur = exec(conn, ['select * from transformedtb where
studentid =' '''' chkid '''']);
cur = fetch(cur);
msgbox('Successful','NF Learner Evaluation');

%----- Fill the temp_input table

```

```

exec(conn,'DELETE from temp_input');
%setdbprefs('DataReturnFormat','cellarray');
colnames = {'ncomplete','ntime','nsubmit','nquiz'};
exdata(1,1)={cur.data(1,6)};
exdata(1,2)={cur.data(1,7)};
exdata(1,3)={cur.data(1,8)};
exdata(1,4)={cur.data(1,9)};
fastinsert(conn,'temp_input',colnames,exdata);

% cur = exec(conn, 'select * from temp_input');
% cur = fetch(cur);
% tempinput = cur.data;

%----- Fill the temp_input_display table
exec(conn,'DELETE from temp_input_disp');
colnames1 = {'studentid','ncomplete','ntime',
'nsubmit','nquiz'};
exdata1(1,1)={cur.data(1,5)};
exdata1(1,2)={cur.data(1,6)};
exdata1(1,3)={cur.data(1,7)};
exdata1(1,4)={cur.data(1,8)};
exdata1(1,5)={cur.data(1,9)};
fastinsert(conn,'temp_input_disp',colnames1,exdata1);

%if exist('temp_input_disp','file') % for every id
chk aggregatetb
% and build tempinput and set the inputtb

```

```

cur = exec(conn, 'select * from temp_input_disp');
cur = fetch(cur);
set(handles.inputtb, 'Data', cur.data);
% end

close(cur);
close(conn);

else
msgbox('No connections', 'NF Learner Evaluation'); %
build tempinput and set the inputtb
end

else
msgbox('No Entry Check Pls', 'NF Learner Evaluation');
uicontrol(handles.studentid); %set focus on
the textbox
end

% --- Executes during object creation, after setting
all properties.
function studentid_CreateFcn(hObject, eventdata,
handles)
% hObject handle to studentid (see GCBO)
% eventdata reserved - to be defined in a future
version of MATLAB

```

```

% handles      empty - handles not created until after
all CreateFcns called

% Hint: edit controls usually have a white background
on Windows.
%           See ISPC and COMPUTER.
if ispc    &&    isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
set(hObject,'BackgroundColor','white');
end

% --- Executes on button press in pushbutton1.
function pushbutton1_Callback(hObject, eventdata,
handles)
% hObject      handle to pushbutton1 (see GCBO)
% eventdata    reserved - to be defined in a future
version of MATLAB
% handles      structure with handles and user data (see
GUIDATA)

global MYCHOICE;
MYCHOICE = 'two';
templist = uigetfile();
if isempty(templist)
msgbox('select a class list pls.' 'NF' 'Learner
Evaluation');
return

```

```

else
if exist(templist,'file')           % for every id chk
transformedtb
% and build tempinput and set the inputtb

templist='classtestingdataset.dat'; %for now
r = importdata(templist);
set(handles.inputtb,'Data',r);

end

end

% --- Executes on button press in pushbutton7.
function pushbutton7_Callback(hObject, eventdata,
handles)
% hObject    handle to pushbutton7 (see GCBO)
% eventdata  reserved - to be defined in a future
version of MATLAB
% handles    structure with handles and user data (see
GUIDATA)
if exist('temp_input_disp','file') % for every id chk
aggregatetb
% and build tempinput and set the inputtb
r = importdata('temp_input_disp');
set(handles.inputtb,'Data',r);
end

```

Appendix B: Sample Moodle Database Tables



Database

moodlelms (314)

- [!\[\]\(58294f689eb2ed4eb49ae75937de3924_img.jpg\) mdl_assign](#)
- [!\[\]\(15ba14f8a3869bd0a1b10778a45f7cf3_img.jpg\) mdl_assignfeedback_comments](#)
- [!\[\]\(5085dfb42e7ee68a0ec9e0a370d3d4db_img.jpg\) mdl_assignfeedback_file](#)
- [!\[\]\(8d0952c93f6fa20b868639c0457b9434_img.jpg\) mdl_assignment](#)
- [!\[\]\(d74086e55e4d69bb33094d80e96c5367_img.jpg\) mdl_assignment_submissions](#)
- [!\[\]\(bd12b3db86409a781c40dd8c2eb1eac7_img.jpg\) mdl_assignsubmission_file](#)
- [!\[\]\(49351f33ed67bff9fce6ab44b1cc031a_img.jpg\) mdl_assignsubmission_onlinetext](#)
- [!\[\]\(fb2388f62e13e57be0d49a09fa8d81d9_img.jpg\) mdl_assign_grades](#)
- [!\[\]\(37bebc843bdedb0dd12e3fabaa6832eb_img.jpg\) mdl_assign_plugin_config](#)
- [!\[\]\(2888cb49cac9488a034ecbc8d03cd1e6_img.jpg\) mdl_assign_submission](#)
- [!\[\]\(f61178c83b671425e119869e2c039417_img.jpg\) mdl_assign_user_flags](#)
- [!\[\]\(5851b2a92f877d8b450d02a87fa5bc56_img.jpg\) mdl_assign_user_mapping](#)
- [!\[\]\(e08d8501f0e1b0474cadf92556f2946b_img.jpg\) mdl_backup_controllers](#)
- [!\[\]\(ec202a27a0bcfbd466472d560add95be_img.jpg\) mdl_backup_courses](#)
- [!\[\]\(ee337f037ebf4c5121a72821163636ed_img.jpg\) mdl_backup_files_template](#)
- [!\[\]\(e7f67fef73166684ecc2277f81c288b6_img.jpg\) mdl_backup_ids_template](#)
- [!\[\]\(79e56f9eb0a86442247910924d77fa46_img.jpg\) mdl_backup_logs](#)
- [!\[\]\(d6174f409a3105a05f674fd457e36804_img.jpg\) mdl_badge](#)
- [!\[\]\(720887b960d81acd28f1df54905880b3_img.jpg\) mdl_badge_backpack](#)
- [!\[\]\(bc44b53e461463b9bb6599238f3ef90f_img.jpg\) mdl_badge_criteria](#)

- [!\[\]\(1012252f3a9f3b9c3b9f9fafd332e3fc_img.jpg\)mdl_badge_criteria_met](#)
- [!\[\]\(149a662b0dd1606d1d428fa82347b3b7_img.jpg\)mdl_badge_criteria_param](#)
- [!\[\]\(ccd657aff81b540ded6546c43d817bb4_img.jpg\)mdl_badge_external](#)
- [!\[\]\(4fb33e4e9858bd47663745e220dbd441_img.jpg\)mdl_badge_issued](#)
- [!\[\]\(bdbdb2455cf994cc2739747bb77f97f4_img.jpg\)mdl_badge_manual_award](#)
- [!\[\]\(07a3846e63987748a3bb5bfc57f931f4_img.jpg\)mdl_block](#)
- [!\[\]\(90d88d395d892669c7ac3a65eb31793f_img.jpg\)mdl_block_community](#)
- [!\[\]\(1f58333f481fca943636a57b26cfd6fd_img.jpg\)mdl_block_instances](#)
- [!\[\]\(3fadbdee5816a609592ccbfea4def94c_img.jpg\)mdl_block_positions](#)
- [!\[\]\(4a13972dd3d5228703cd89139ea67d8c_img.jpg\)mdl_block_rss_client](#)
- [!\[\]\(d3b69834ef38f4859c83c0980cc29a0c_img.jpg\)mdl_blog_association](#)
- [!\[\]\(b2295d0241f60087879b3f82fed35de9_img.jpg\)mdl_blog_external](#)
- [!\[\]\(55a391d7babcd7a0eba05ffb60891299_img.jpg\)mdl_book](#)
- [!\[\]\(052779a6164f0503448e2d68fe4e7d85_img.jpg\)mdl_book_chapters](#)
- [!\[\]\(38fb20d324593b148027097228807043_img.jpg\)mdl_cache_filters](#)
- [!\[\]\(04d696bb6a2f19db25a3dc9b660c8185_img.jpg\)mdl_cache_flags](#)
- [!\[\]\(543763cbad38e4100633cdbc49e64fdd_img.jpg\)mdl_cache_text](#)
- [!\[\]\(18811efa695e7c13e277a1f636a0435f_img.jpg\)mdl_capabilities](#)
- [!\[\]\(b384e478ce0f9438f80c796b21645a78_img.jpg\)mdl_chat](#)
- [!\[\]\(26f60c874e36dd1fe60fdd38fd535eae_img.jpg\)mdl_chat_messages](#)
- [!\[\]\(8c002fb8be97af56524ac242b81d7c7a_img.jpg\)mdl_chat_messages_current](#)
- [!\[\]\(2dcd40cf53a66a6a6313683259b252bd_img.jpg\)mdl_chat_users](#)
- [!\[\]\(841872c72ab1e06a846fad5fe5f4517d_img.jpg\)mdl_choice](#)
- [!\[\]\(9f1574ac7c04b1009fe59904b92e1df1_img.jpg\)mdl_choice_answers](#)
- [!\[\]\(d578568d51f915b654f18bf106d86351_img.jpg\)mdl_choice_options](#)
- [!\[\]\(bca39766654b56c7e14ab5d408578b6f_img.jpg\)mdl_cohort](#)
- [!\[\]\(483f2e81cdf423916d8b012aeba29fd4_img.jpg\)mdl_cohort_members](#)

- [!\[\]\(da961f281a595c894aed5c132dc8f450_img.jpg\)mdl_comments](#)
- [!\[\]\(94226ae311b434de473c1888c1675fc2_img.jpg\)mdl_config](#)
- [!\[\]\(0ae88ba1fd32509bcd369a379d8c8988_img.jpg\)mdl_config_log](#)
- [!\[\]\(3344421f654329a96900f4330ac8d1cd_img.jpg\)mdl_config_plugins](#)
- [!\[\]\(e28228c5754b93ad769dfa120ef0a5d4_img.jpg\)mdl_context](#)
- [!\[\]\(74c4494912eb80a59f94db45ece5c4b1_img.jpg\)mdl_context_temp](#)
- [!\[\]\(ea5ea232631abcfc72a79d0c9818da4c_img.jpg\)mdl_course](#)
- [!\[\]\(7eb0c9a0ef90dfdbc4928fef8c8150a4_img.jpg\)mdl_course_categories](#)
- [!\[\]\(e32fc33fc800c96bf8b9dc4eefdedf22_img.jpg\)mdl_course_completions](#)
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- [!\[\]\(49a3076734a84877e0f3172810bd47c2_img.jpg\)mdl_course_modules_availability](#)
- [!\[\]\(ccdaef1230fefdb7a4335ba5439666e8_img.jpg\)mdl_course_modules_avail_fields](#)
- [!\[\]\(0d04627c36e2d41e393c965b5d853538_img.jpg\)mdl_course_modules_completion](#)
- [!\[\]\(0fd1deb1d064fcdafe9a7bd22afc6795_img.jpg\)mdl_course_published](#)
- [!\[\]\(2bd4db0893d20712745fbc7b0bd26a38_img.jpg\)mdl_course_request](#)
- [!\[\]\(8cb287a2b6a440de96af9861ca560ff5_img.jpg\)mdl_course_sections](#)
- [!\[\]\(ab4047f9c26ccd40debcfa8df613441c_img.jpg\)mdl_course_sections_availability](#)
- [!\[\]\(878ff2792ace6730b4f62b5b61f91eff_img.jpg\)mdl_course_sections_avail_fields](#)
- [!\[\]\(09d2d4c55ba8ce5fe8996222eef49288_img.jpg\)mdl_data](#)
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- [!\[\]\(319d61e2bdf84d7d977d6eaabcee01d5_img.jpg\)mdl_enrol_authorize_refunds](#)
- [!\[\]\(78159a2a63985e3eccfca347af4c3c13_img.jpg\)mdl_enrol_flatfile](#)
- [!\[\]\(c358da7302eb1ef190d173a2410cc2b3_img.jpg\)mdl_enrol_paypal](#)
- [!\[\]\(97548cd2449c566d78aac700a9a3015d_img.jpg\)mdl_event](#)
- [!\[\]\(3df03144523a23357d857d3e6f52a626_img.jpg\)mdl_events_handlers](#)
- [!\[\]\(4a723897c3b31b120c64c4b5bcbde87f_img.jpg\)mdl_events_queue](#)
- [!\[\]\(93c74be53a506e3a9c00f5c200808cba_img.jpg\)mdl_events_queue_handlers](#)
- [!\[\]\(166b4cba0e97afb9a66a93f7ddc3b3ea_img.jpg\)mdl_event_subscriptions](#)
- [!\[\]\(ee350e574b886ab226a21135254d0761_img.jpg\)mdl_external_functions](#)

(10) What would you want improved in the Blended learning approach been employed?

- I want to improve my knowlege on system analysis and design so that i can be able to interact with my course mates
 - I want to improve my knowledge in system analysis and design
 - If possible, implementing an audio chat room or skypeing among the students when logged in
 - We need to be guided sometimes, the lecturer should come around once in a while to put us through since this is our first time of e-learnin
 - interactive sessions between the instructor and the students
 - Even though the blended learning approach is okay, I'd love it if we could have class interactions with the lecturer like every two weeks to enlightened us more about system analysis and design.
 - letting us see what is been posted by on the forum by our other classmate.
 - less assignment, lecturer should please come to class at least once in two weeks to explain to students
 - understand the course but not just searching and reading on the course
 - more lecture notes and references
 - more frequent classes
 - Video and audio lectures, more course materials from the lecturer
 - i will like you to hold more classes every week for better understanding of all the assigment giving to us.
-

- Nothing really

- some real life classes should be introduced to cover or discuss what we have covered online

- The session time-out is too short

- We should improve the lecturer student interaction, so as to communicate well with our lecturer.

- I will have to find a way of connecting other people around the world to this Blended learning approach to share their point of view and ideas and also try to put some search engine of the site for a fast learning.

- it would have been a great approach if the internet service is always available...So if the internet service is always available, it would have been better

- addition of a search engine

- it is easily but not like having the material to read because it is not everybody that can read on laptop.

- to me Its perfect not stressful and easy. to understand

(11) What are the challenges you have using the platform?

- The only challenges is the internet net work

- Nothing

- 1. The university network 2. No interaction between student on the platform, so u have to look for someone to explain some concept of the course

- The platform is not user friendly!

- I don't really have any challenge with the platform. The only problem I have is

on internet connection, the school's internet service is kind of poor.

-
-
- searching online and library for the answer to the questions given at times
-
-
- poor wireless, network problem in malete area, (using modem), less internet cafe in malete area
-
-
- bad network, no standard internet cafe, school wifi not connecting always
-
-
- internet access problem
-
-
- Complex User Interface
-
-
- Poor Internet around school Enviroment
-
-
- poor internet facilities and itr is not user friendly so it need to be more interactive for the user.
-
-
- The main challenge is the issue of network
-
-
- majorly internet access but it also affects the time I dedicated for other courses. I tend to spend most of my time doing one thing or the other on this course
-
-
- The schoool network and unavailability of teacher to put me tru
-
-
- The only challenge I had was when I wanted to submit my last gathering of materials using NWIKi, I was unable to upload an image. Else that, the platform is okay and great.
-
-
- I dont see anything as challenge but as a new thing which I have to know before leaving the university or passing this course.
-
-
- none
-
-
- slow interest access
-
-
- the challenges i have is that i have never did any program online.
-
-

-
- network Was my main problem
-
-
- how to browse and search for the materials at times.
-
-
- server problem
-
-
- 1. Poor Network. 2. Unable 2 find answer to some questions easiliy
-
-
- Am having network problem because sometimes i usually have difficulties in opening and submitting my assignments.
-

Appendix D. Published Peer Review Articles and Conference Presentations

Published Peer Review Articles:

- i. Omidiora, E.O., Olabiyisi, S.O., Okediran, O.O and **Isiaka, R.M.** (2013); Learner Activities Evaluation: A Neuro Fuzzy Approach. *International Journal of e-Education, e-Business, e-Management and e-Learning (IJEEEE, ISSN: 2010-3654)*. IACSIT Press, Jurong West, Singapore. 640708, Tel: +65-31563599, <http://www.iacsitp.com>, email: pub@iacsit.org

- ii. **Isiaka, R.M.**, Omidiora, E.O., Olabiyisi, and S.O., Okediran, O.O (2014); Mamdani Fuzzy Model for Learning Activities Evaluation. *International Journal of Applied Information Systems (IJ AIS) – ISSN: 2249-0868 Foundation of Computer Science FCS, New York, USA. Volume 7– No.3, May 2014 – www.ijais.org*.

- iii. **Isiaka, R.M.**, Omidiora, E.O., Olabiyisi, and S.O., Okediran, O.O (2015); An Enhanced Learning Technology System Architecture for Web-Based Instructional Design. *International Journal of Emerging Technologies – ISSN: 1863-0383 International Association of Online Engineering, Vienna Austria* – <http://online-journals.org/index.php/i-jet> . (Article in Press)
- iv. **Isiaka, R.M.**, Omidiora, E.O., Olabiyisi, and S.O., Okediran, O.O., R.S. Babatunde (2015); Mamdani, Sugeno and Anfis E-learners Activities Models: A Comparative Study. *Transactions on Machine Learning and Artificial Intelligence – ISSN: 2054-7390 Society for Science and Education, UK* – <http://tmlai.scholarpublishing.org> (Article in Press)

Conference Presentations:

R.M. Isiaka, “Development of Students E-Learning Activities Exploration Model Using Neuro-Fuzzy Approach” , Research Consortium on Information Technology Innovations (ReCITI 2013) parallel session 6 page 27, Nigeria Computer Society (NCS) – 11th International Conference on e-Governance & National Security. July 24-26, 2013, Royal Park hotel, Iloko Ijesa, Osun State, Nigeria.

Isiaka, R.M., Omidiora, E.O., Olabiyisi, and S.O., Okediran, O.O., “An Enhanced Learning Technology System Architecture for Web-Based Instructional Design”, Application of Information and Communication Technologies to Teaching, Research and Administration (AICTTRA 2015) - 9th International Conference on ICT Applications, September 13-17, 2015, Kwara Hotels, Ilorin

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