Chapter Six

Optimization and Evaluation

6.1 Introduction

Optimization is a continuous process that happens iteratively and recursively to achieve better: addressing and understanding the problems in hand, presenting different proposed solutions, optimizing the selected solution, applying the optimized and enhanced solution, evaluating the applied solution, and then back to the beginning of the optimization lifecycle. Optimization lifecycle is presented in figure 6.1. In this chapter, we review what we have presented through the dissertation quickly and focus on evaluation and optimization aspects of the proposed Adaptive e-Learning Models and Intelligent Services.

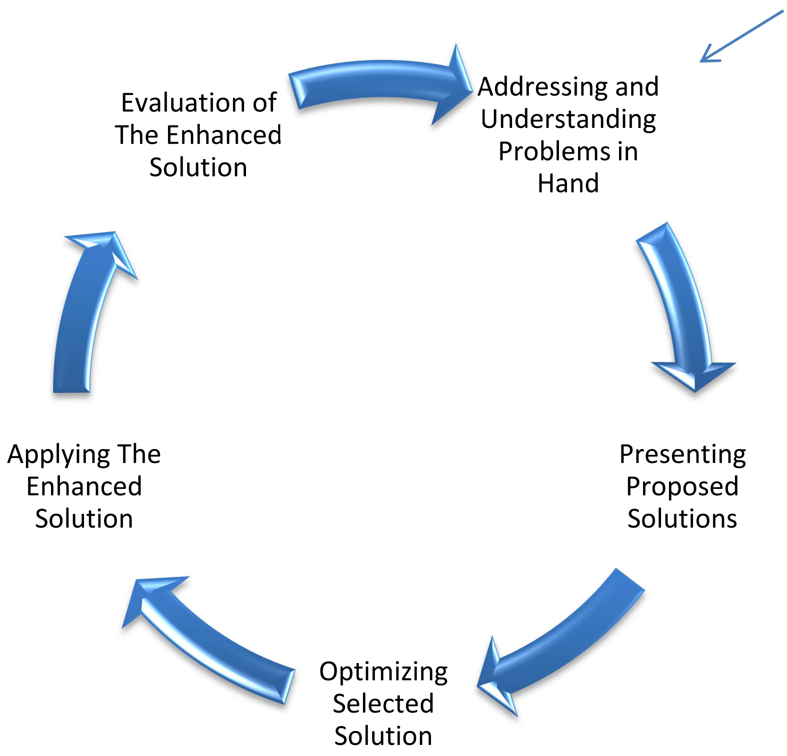

Figure 6.1: Optimization Lifecycle

6.2 Addressing Problems

Proposed Adaptive e-Learning Models addressed two problems categories: Technical and Pedagogical problems.

6.2.1 Pedagogical Problems

Reviewing current e-Learning status shows that current Blended Learning Model Paradigm faces many challenges; mainly pedagogical. To take a closer look at the problem, we conducted a pilot study for fourth year Information Systems department students at the faculty of Computers and Information Sciences in Mansoura University, Egypt, later at 2008. The good thing is that students believe in the efficiency of e-Learning and they are willing to use e-Learning and participate in e-Learning experiments, however there were problems. Pedagogical problems include:

- Students don’t use internet as their source of information although Internet is the main updated source of information and needs to be integrated in the learning environment.
- Most Students don’t know what “Tutorials” is. That means they haven’t utilized an online learning resources in a sequenced manner that helps them learn new topics at the end of a certain stage.
- Most students don’t access internet via their mobile phones, and they are not willing to participate in mobile learning experiments. They even believe mobile learning will not become popular in the near future.
- Students agreed that we utilize different forms of e-Learning. Though the faculty of the authors does not provide an official site for e-Learning, any online courses, assessment site or any other form of e-Learning other than the

authors' attempts, students still believe that e-Learning is efficient - even if they have not experienced it at all.

For more details about the pilot study, the reader can refer to chapter 3.

6.2.2 Technical Problems

Integrating University Management Information Systems (UMIS) and Learning Management Systems (LMS) is a need to achieve better e-Learning systems. Different software architecture patterns can be utilized in integrating both systems. Studying and analyzing many of the available software architectures has led to the realization of efficiency and effectiveness of utilizing Service Oriented Architecture (SOA) however it has led to different challenges. Challenges include the lack of performance efficiency when transmitting large amount of data. Besides, efforts of presenting adaptive and intelligent features of e-Learning have been spent without integration and presentation in current e-Learning systems. Web Service Software Factory design pattern as an example of Web services design patterns that builds everything within systems as Web services will yield to big performance degradation to proposed integrated e-Learning systems. Another technical optimization includes utilizing another integration technologies rather than Web services.

6.3 Presenting Proposed Solutions

Keeping the focus on Web and Desktop applications and shifting away from mobile learning is a direct result of students' unwillingness to experience and participate in mobile learning experiences. The pedagogical solutions focus on introducing adaptive and intelligent features in e-Learning to reach personalized environment. While the technical solutions focus on utilizing SOA in presenting those features. However, we still provide capability to integrate mobile learning activities using SOA.

6.3.1 Pedagogical Solutions

Different adaptive and intelligent pedagogical e-Learning solutions are presented to enable personalized e-Learning environment that will enhance students' e-Learning experience. The need for a personalized e-Learning system that incrementally and gradually takes students through an e-Learning experience is clear from the problems in hands section.

6.3.1.1 Adaptive Pedagogical Solutions

There are four main approaches that can be used to give a historical overview of Adaptive e-Learning. They are *Macro Adaptive*, *Aptitude-Treatment Interaction* (ATI), *Micro-Adaptive* and *Constructivistic-Collaborative* approaches. Proposed adaptive e-Learning model proposed in chapter three addresses those different adaptive e-Learning approaches and utilizes all of them. The four addressed approaches are:

- **Macro Adaptive Approach:** The proposed model addresses this capability by testing the student profile and learning preferences before establishing learning material.
- **Aptitude-Treatment Interaction (ATI) Approach:** The proposed model addresses allows the students to choose among the topics to learn (within the constraints of the pre-requisites). This gives them the partial control experience. Also, the proposed model provides the capability to arrange meetings between the instructors and students that have issues with certain learning topics. Students are given the chance to self-study the subjects and attend the exams 3 times. If the student fails to pass the exam 3 times, a

meeting must be arranged between the instructor and the student to submit a repost by the instructor to the student profile, so the student can continue the learning process again in the adaptive way. This sort of blended learning gives strength to the proposed model.

- **Micro-Adaptive Approach:** The proposed model addresses this approach by providing the capability to calculate the required time to study for each learning topic.
- **Constructivistic-Collaborative Approach:** Online forum, wiki and blog services will be available to students to enhance collaborate and help each other. Facilities to enable online study groups - like chatting applications - can be made available. Arguments around the effectiveness of Web 2.0 features in e-Learning are taking place all around.

6.3.1.2 Intelligent Pedagogical Solutions

Intelligent techniques are presented to empower the proposed Adaptive e-Learning Models. Proposed models shed lights on supporting e-Learning with intelligent features. One of the main features supported by our model is supervised intelligent curriculum sequencing to present adaptive e-Learning fine-tuned by the instructor. Nine intelligent services that can be utilized in different e-Learning functionalities were presented. These intelligent services are grouped into two categories based on their aims: *Instructor Services* and *Student Services*.

The Instructor Intelligent Services are: *Intelligent Learning Object (LO) Classifier service, Intelligent Online Lecture LOs Advisor*, *Intelligent Student Performance Tracker and Intelligent Cheating Depressor.* The Student Intelligent Services are: *Intelligent Time-to-Learn Topic Calculation, Intelligent*

Study Plan Advisor, *Intelligent Agenda Study Time Planner*, *Intelligent Meeting Manager for Suspended Students and Intelligent LOs Recommender*.

Fuzzy Logic is the intelligent technique used in different aspects of the services to enable different functionalities as presented in chapter four.

6.3.2 Technical Solutions

Combining both Business Process Management (BPM) and Service Oriented Architecture (SOA) is proven to achieve numerous advantageous features for systems. Presenting adaptive and intelligent features as services with standard interfaces will allow different e-Learning systems to adopt them, so they will be reusable and newly introduced information systems will not have to redo the work again, besides, wrapping adaptive and intelligent features with standard interfaces will present a separation of interests that help adaptive and intelligent features' researchers and developers to focus more on their target and transfer the responsibility of utilizing those features in different information systems to information systems specialists. Presented Adaptive e-Learning Models presented an adaptive learning process that adaptively changes based on students' performance. Proposed model composing services can be categorized in the following layers:

- **Orchestration Layer:** holds services responsible for maintaining learning process logic and activities. It includes services that utilize both composite services' layer services, and data services' layer services.
- **Composite Services:** are services that hold other services and don't complete functioning unless all composing services execute successfully; however it is not controlling them.
- **Data Services Layer (Information as a Service "IaaS"):** is the layer that holds services responsible for transforming Meta-data into meaningful information to other utilizing information systems, instructors, and students.

- **Model Layer (Database):** it is the database layer that holds data tables.

Though Web services provide technology neutral interface to be utilized online through standard URL, J2EE Connector Architecture (JCA) connects Java based applications in an enhanced performance measures when compared to XML Web services. Another technical optimization point includes using emerging protocols that are designed for Web. The Open Data Protocol (OData) is a web protocol for querying and updating data. OData applies web technologies such as HTTP, Atom Publishing Protocol (AtomPub) and JSON to provide access to information from a variety of applications, services, and stores. OData is being used to expose and access information from a variety of sources, including but not limited to relational databases, file systems, content management systems, and traditional web sites.

6.4 Optimizing Selected Solution

Applying the presented solution yielded some challenges and bottlenecks that need optimization. Optimization in this phase focuses on the system performance. Intelligent LOs Recommender is the one of the core services and lies in the heart of the proposed Adaptive e-Learning Models. It is utilized in different intelligent services. However, upon deployment, Intelligent LOs Recommender met challenges that affected its performance and efficiency. Optimizing it will affect the presented models overall performance. Intelligent LOs Recommender is evaluated from Performance perspective in order to accelerate overall system performance.

6.4.1 Intelligent LOs Recommender Challenges

To empower the presented adaptive e-Learning models, we designed and built the Intelligent LOs Recommender. Intelligent LOs Recommender was tested on different files (221) and online LOs (342). Files LOs generated 7388 tokenized Term Frequencies (TF) and online LOs generated 169876 TFs. Challenges in designing and implementing the Intelligent LOs Recommender include:

1. **Identifying Seeds:** with the increasing number of online content, defining seeds for the crawler is an important task.
2. **Identifying Online and Offline Phases:** identifying bottlenecks in the Intelligent LOs Recommender performance is an important issue to avoid dead ends and long times of processing that affects systems.
3. **Evaluating Accuracy of Generated Terms:** generated terms shall be evaluated to avoid non-related terms.

Unleashing an online crawler to collect different LOs available online, and storing meta-data about them in an offline database, with URLs made available for later visits of the Intelligent LOs Recommender service was the first task achieved in building this service. Visiting those URLs later, retrieving the LOs, tokenizing and stemming, calculating Term Frequencies, and storing calculated Term Frequencies in the database for later matching with course objectives. Random LOs group of the crawlers results are used as the test set with capacity of 254 LOs. Reading time in seconds for each of those LOs are presented in Figure 6.2. Table 6.1 presents summary of the main statistical measures of LOs reading times in seconds.

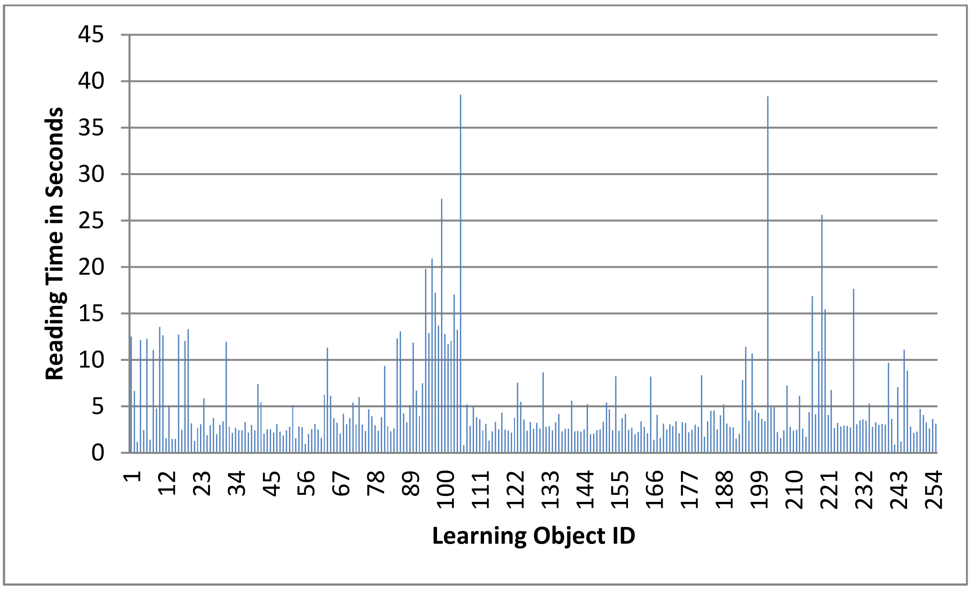

Figure 6.2: Learning Objects Reading Time in Seconds

Table 6.1: Summary of the Main Statistical Measures of Learning Objects Reading Times in Seconds

Min.	0.819568872	**Mean**	5.108815395
Max.	38.5457058	**Mode**	N/A
Range	37.72613692	**Median**	3.159333944

Reading times fall in an average time of five seconds in retrieving the LO. Optimizing LOs retrieval can be done through increasing network bandwidth and the servers' memory that affects window sizing. Tokenization duration for retrieved LOs is presented in Figure 6.3 followed by Table 6.2 summarizing the main statistical measures of tokenizing LOs times in seconds. Tokenization duration falls below half a second at its worst case, and it is believed that tokenization is in an optimized form.

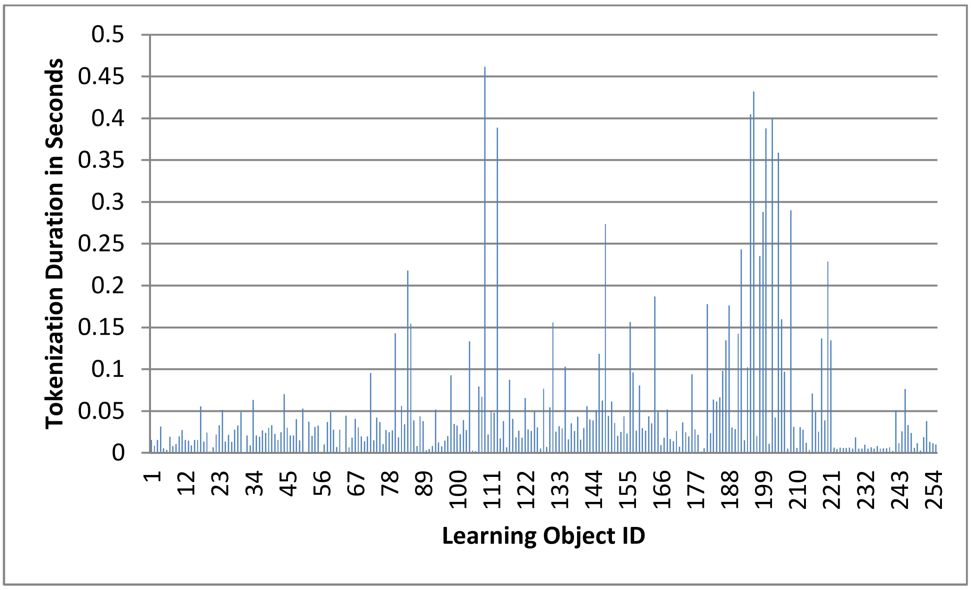

Figure 6.3: Learning Objects Tokenization Duration in Seconds

Table 6.2: Main Statistical Measures of Learning Objects Tokenization Times in Seconds

Min.	0.000496149	**Mean**	0.051718733
Max.	0.461540937	**Mode**	N/A
Range	0.461044788	**Median**	0.026743531

Term Frequencies calculation time for each LO is presented in Figure 6.4 followed by Table 6.3 that highlights a summary of the main statistical measures of Learning Objects Term Frequencies calculation time in seconds. TF processing ranges are from fractions of milliseconds to less than three seconds for the LO. TF processing is efficient enough to be utilized in the recommendation process.

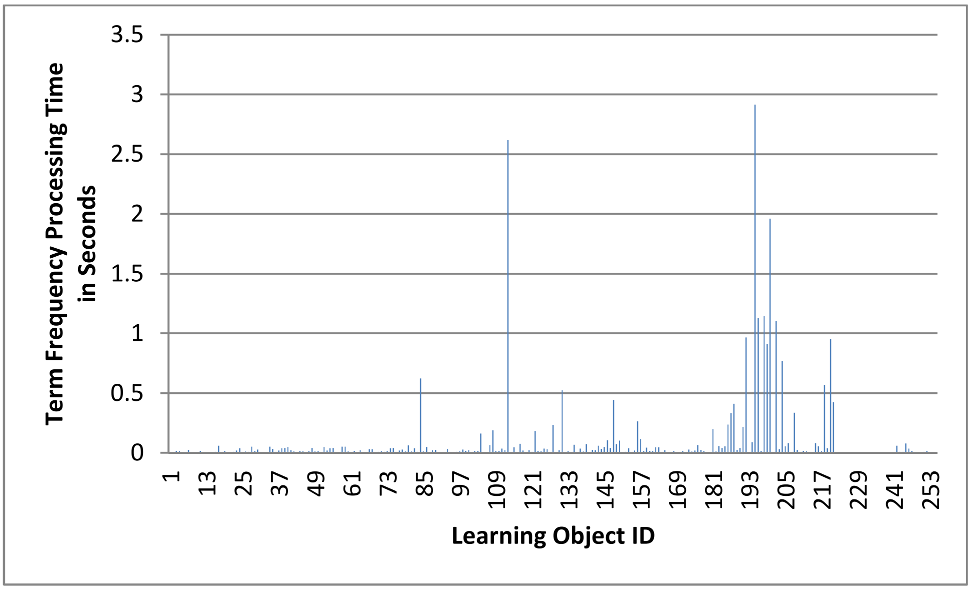

Figure 6.4: Learning Objects Term Frequencies Calculation Times in Seconds

Table 6.3: Main Statistical Measures of Term Frequency Calculation Time in Seconds

Min.	6.48499E-05	**Mean**	0.095572824
Max.	2.913298845	**Mode**	0.001230955
Range	2.913233995	**Median**	0.015192032

The first performance bottleneck appears in extracted terms database insertion times. Figure 6.5 presents LOs keywords insertion time in seconds. As summarized in Table 6.4, average keywords insertion time for LO is 373 seconds, with worst cases exceeding 2536 seconds. Such performance issue is not accepted and leading to dead ends in the system. It takes a lot of time to insert keywords in the database for later recommendation processing.

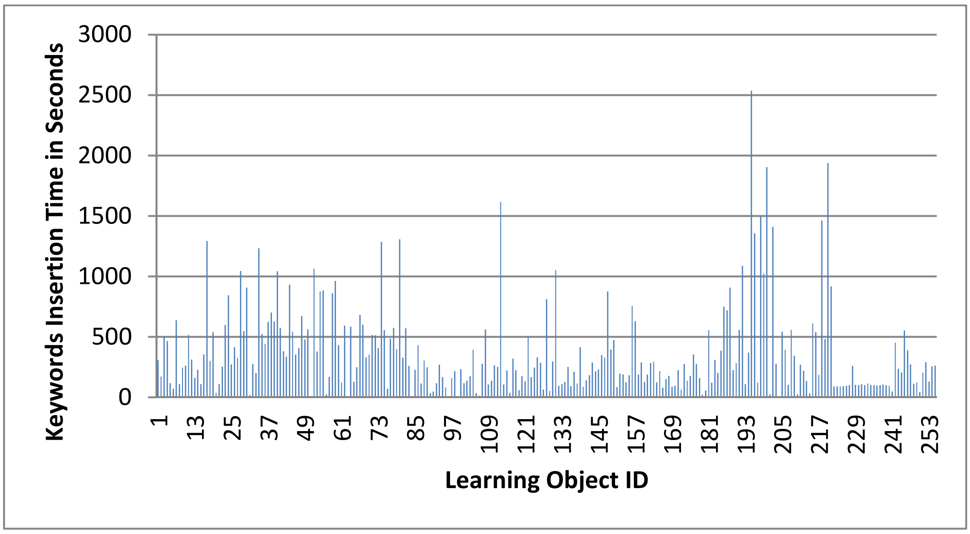

Figure 6.5: Learning Objects Keywords Insertion Times in Seconds

Table 6.4: Main Statistical Measures of Learning Objects Keywords Insertion Time in Seconds

Min.	4.576031208	**Mean**	373.0938357
Max.	2536.919661	**Mode**	N/A
Range	2532.34363	**Median**	260.3440971

Figure 6.6 compares the percentage that tokenized number of words and the total number of words contributes to the total. Tokenized number of words when compared to total number of words doesn’t exceed 15% by anyhow. One challenge with online LOs is the tremendous amount of Hyper Text Markup Language (HTML) used for web based user interface. Tokenization process is responsible for handling this challenge. Regular Expressions (RE) are used to extract text from online LOs. Tables 6.5 and 6 present statistical measures about total and tokenized number of words respectively.

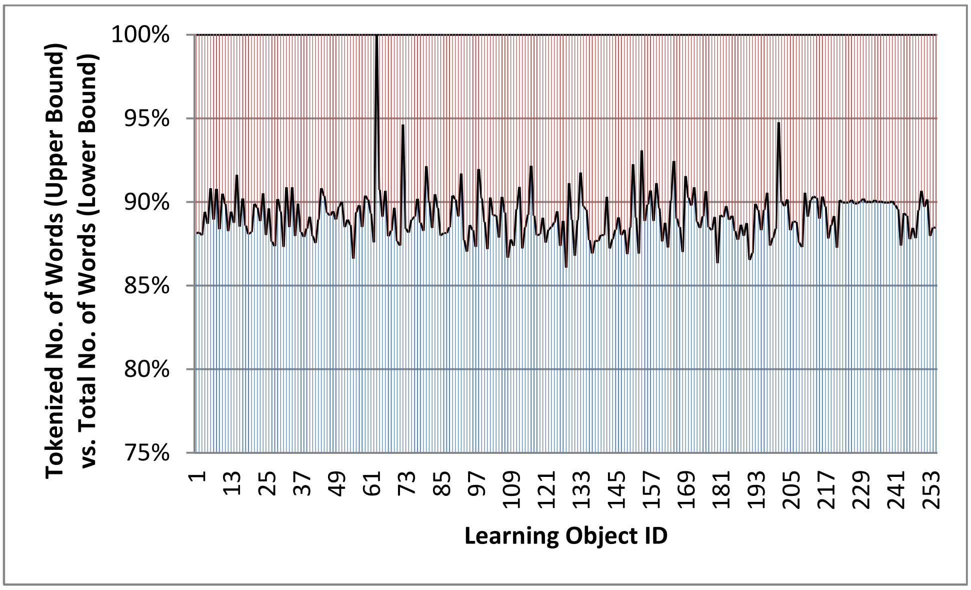

Figure 6.6: Learning Objects Tokenized No. of Words vs. Total No. of Words

Table 6.5: Main Statistical Measures of Learning Objects Original No. of Words Count

For Total Learning Object Words			
Min.	5	**Mean**	7238.443137
Max.	66491	**Mode**	1085
Range	66486	**Median**	3803

Table 6.6: Main Statistical Measures of Learning Objects Tokenized Number of Words Count

For Tokenized Words			
Min.	0	**Mean**	912.6745098
Max.	9737	**Mode**	121
Range	9737	**Median**	469

Though tokenized number of words percentage when compared to total number of words doesn't exceed 15%, there is still a challenge facing our proposed Intelligent LOs Recommender which is the tremendous amount of extracted keywords that is not related to course objectives. Processing books for example, is a big challenge. One of the processed books was read in less than 0.25 a second with 12522837 original words number, generated 258457 tokenized words (1.6 MB of data) in 2188 seconds for tokenization processing, and Term Frequency calculation of 521 seconds. Such processing never finished uploading extracted keywords into the database.

Situation changes a lot when adding the course objectives into inputs. Course objectives extracted keywords and expanded by WordNet to increase system's efficiency percentage when compared to number of tokenized words and total number of words is presented in Figure 6.7. Handling more than the really needed keywords yields a big performance degradation that we can get rid of by presenting a design solution and taking the decision of including course objectives as an input parameter, thus coming over the performance bottleneck. Figure 6.8 followed by Table 6.7 presents the optimization gained in insertion.

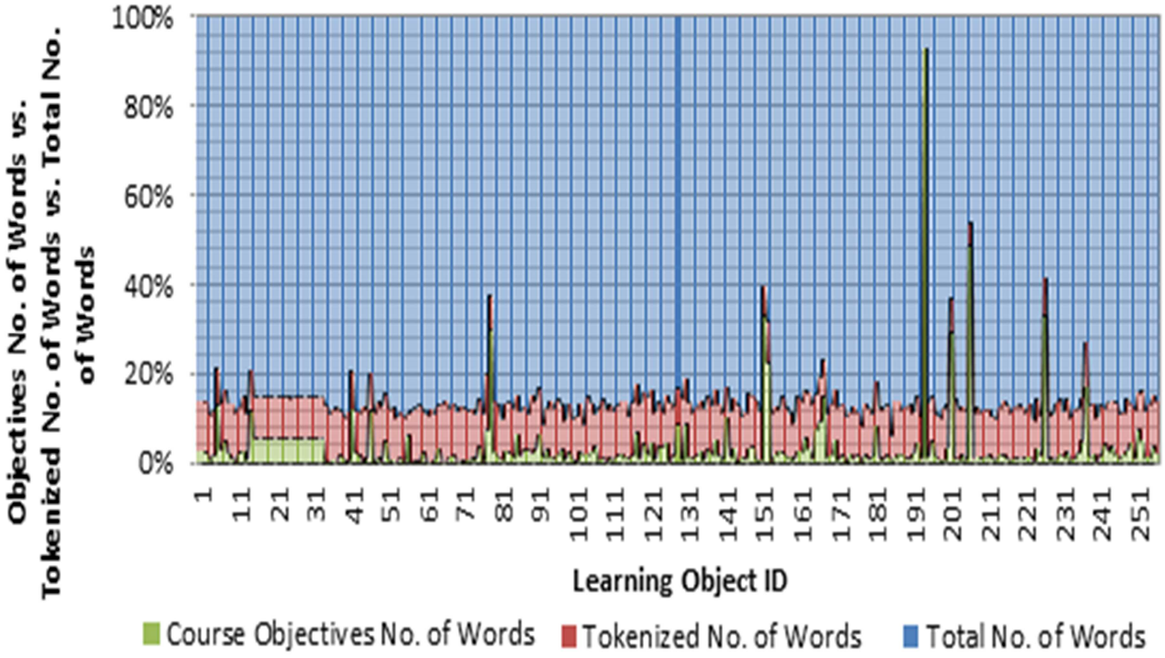

Figure 6.7: Course Objectives Extracted and Expanded Keywords vs. Tokenized No. of Words vs. Total No. of Words

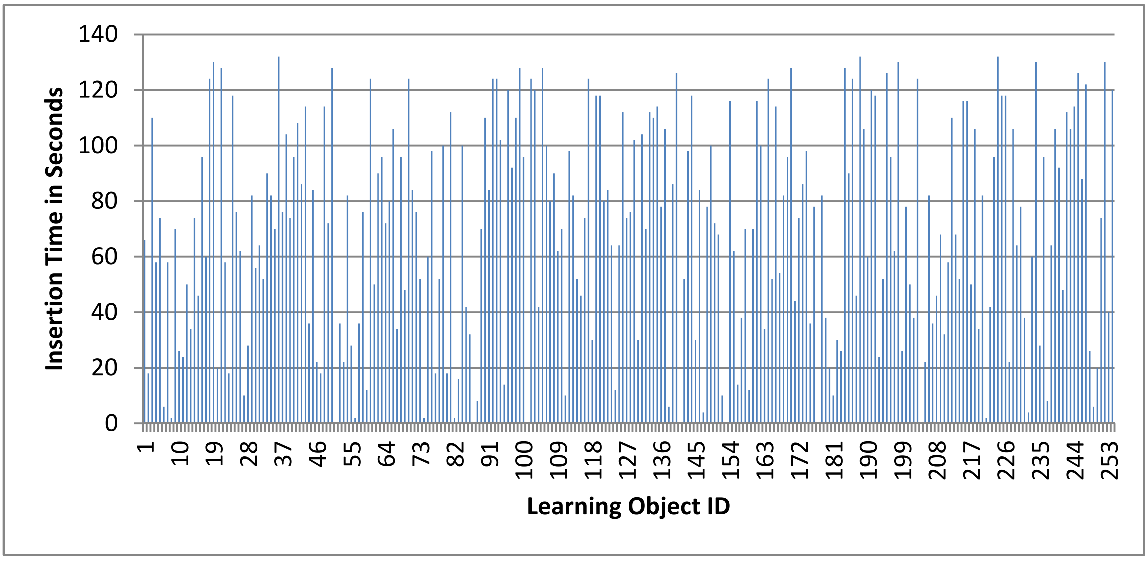

Figure 6.8: Learning Objects Optimized Keywords Insertion Times in Seconds

Table 6.7: Main Statistical Measures of Learning Objects Keywords Insertion Time in Seconds

Min.	0	**Mean**	124
Max.	132	**Mode**	N/A
Range	132	**Median**	74

6.4.2 Intelligent LOs Recommender Optimization Techniques and Comments on Results

Optimizing and Enhancing the Intelligent LOs Recommender can be done through different design decisions:

- **Taking course objectives into consideration while determining crawler seeds:** a preprocessing step that processes course objectives and generate search keywords that are used to find related web sites using one of the many internet search engines helps in finding more near and accurate seeds for the crawler. In our proposed model, we developed a java based crawler that takes course objectives keywords as input, uses Google search engine to invoke the search query, loops through search results, and stores meta-data about found URLs in the database.
- **Query Expansion:** to increase the accuracy of search terms resulting from processing course objectives and specifications, query expansion methods

can be utilized. WordNet is a lexical database for the English language that groups English words into sets of synonyms to provide short, general definitions, and records the various semantic relations between these synonym sets. Extracted keywords are expanded by WordNet synonyms and then passed to the crawler when seeking seeds.

- **Taking course objectives into consideration while calculating Term Frequencies for Learning Objects:** the main objective of Intelligent LOs Recommender is to intelligently contribute in personalizing the learning experience for the student by recommending the most accurate LOs, not indexing the online LOs. So, there is no need to get stuck in analyzing what doesn’t matter for the recommendation process. Enhanced solution will not calculate frequencies for terms that don’t exist in curse objectives and will not store term frequencies at all. The processing time and cost is much cheaper when compared to storage cost.

6.5 Evaluating Optimized Solution

Presented Adaptive e-Learning Models and Intelligent Services shall be evaluated from different perspectives. Evaluation perspectives include:

1. **User Satisfaction:** Users here are both students and instructors.
2. **Information Retrieval** Evaluation of Intelligent LOs Recommender.
3. **Intelligent LOs Classifier** Evaluation.

Following sections present those three evaluation aspects and results.

5.1 User Satisfaction Evaluation

Preparing a Computer Networks Course and presenting it to students in the form of the presented Adaptive e-Learning Models and experiencing it, resulted in the following satisfaction measures. Table 6.8 presents summary of students' opinion about presented features and how they evaluate the need for it and its performance. Presented Adaptive e-Learning Model was tested on sample of 10 students. Table 6.9 presents summary of instructors' thoughts about presented features and how they evaluate the need for it and its performance and behavior.

Table 6.8: Summary of Students' Evaluation of Presented Adaptive e-Learning Models Features

Feature	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Learning Preferences	90%	10%	--	--	--
Learning Profile	85%	15%	--	--	--
Customizing Course within Rules	80%	10%	10%	--	--
Separate Groups	30%	10%	10%	25%	25%
Exams Check Points	30%	10%	10%	30%	20%
LVQ	90%	5%	5%	--	--
Video LOs	90%	5%	5%	--	--
Intelligent LOs Recommender	70%	20%	--	5%	5%
Intelligent Agenda Study Time Planner	63%	17%	5%	8%	7%
Intelligent Study Plan Advisor	65%	30%	--	5%	--
Intelligent Meeting Manager for Suspended Students	40%	10%	8%	2%	40%

Table 6.9: Summary of Instructors' Evaluation of Presented Adaptive e-Learning Models Features

Feature	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Learning Preferences	90%	10%	--	--	--
Learning Profile	90%	10%	--	--	--
Customizing Course within Rules	90%	10%	--	--	--
Separate Groups	70%	20%	10%	--	--
Exams Check Points	70%	15%	15%	--	--
LVQ	90%	5%	5%	--	--
Video LOs	90%	5%	5%	--	--
Intelligent LOs Recommender	70%	20%	10%	--	--
Intelligent Online Lecture LOs Advisor	73%	17%	10%	--	--
Intelligent Cheat Depressor	50%	10%	10%	20%	10%
Intelligent Student Tracker	80%	20%	--	--	--

6.5.2 Information Retrieval Evaluation

One of the fundamental problems in Information Retrieval (IR) is the ranking problem, ordering the results of a query such that the most relevant results show up first. Ranking algorithms employ scoring functions that assign scores to each result of a query at hand. So, ranking the results of a query consists of assigning a score to each result and then sorting the results by score, from highest to lowest. Many performance measures are used by IR community to evaluate the effectiveness of ranking functions.

In order to measure the relevance of the Ranked Recommended LOs list, three performance measures are used namely: Precision, Recall, and F-measure. The first performance measure used is Precision. Precision measures the ratio of relevant documents within a given number of documents returned to the number of returned documents. The second performance measure is Recall. Recall is defined as the number of relevant documents retrieved by a search divided by the total number of existing relevant documents (which should have been retrieved). The Recall measure quantifies what fraction of all the relevant results was ranked to fall within the first k documents. Precision and Recall scores are not discussed in isolation. Instead, both may be combined into a single measure, such as the F-Measure. F-Measure is the weighted harmonic mean of precision and recall. Figure 6.9 shows the precision measures of the proposed Intelligent LOs Recommender followed by Table 6.10 highlighting a summary of the main statistical measures. Figure 6.10 shows the recall measures of the proposed Intelligent LOs Recommender followed by Table 6.11 highlighting a summary of the main statistical measures. Figure 6.11 shows the F-Measure of the proposed Intelligent LOs Recommender followed by Table 6.12 highlighting a summary of the main statistical measures.

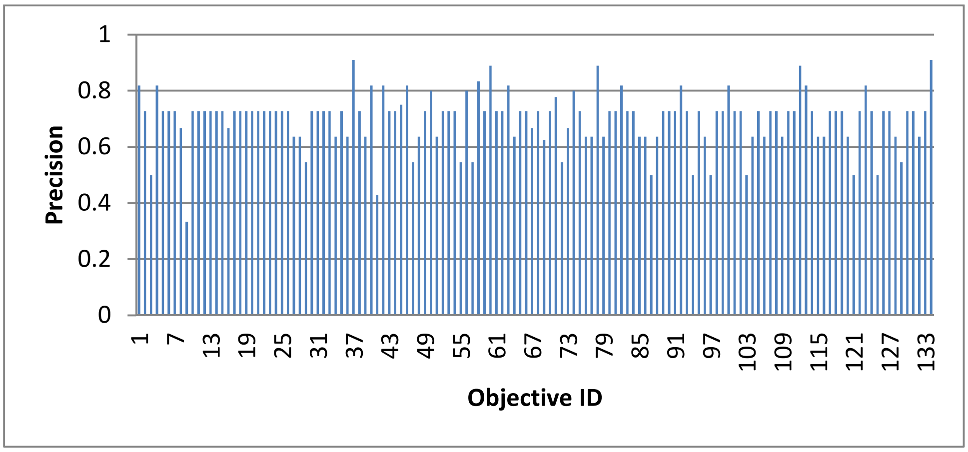

Figure 6.9: Precision Evaluation of Proposed Intelligent LOs Recommender

Table 6.10: Summary of the Main Statistical Measures of Precision

Min.	0.333333333	**Mean**	0.700674926
Max.	0.909090909	**Mode**	0.727272727
Variance	0.008883086	**Median**	0.727272727

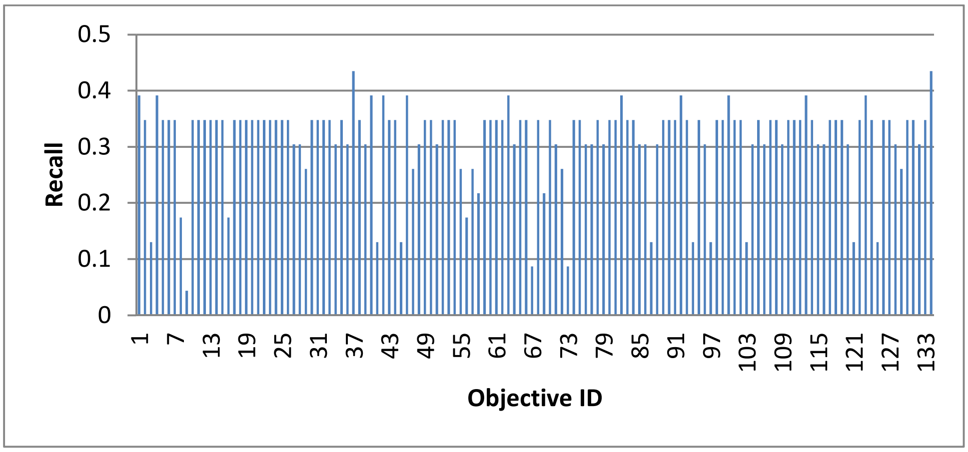

Figure 6.10: Recall Evaluation of Proposed Intelligent LOs Recommender

Table 6.11: Summary of the Main Statistical Measures of Recall

Min.	0.434782609	**Mean**	0.31440623
Max.	0.434782609	**Mode**	0.347826087
Variance	0.005640442	**Median**	0.347826087

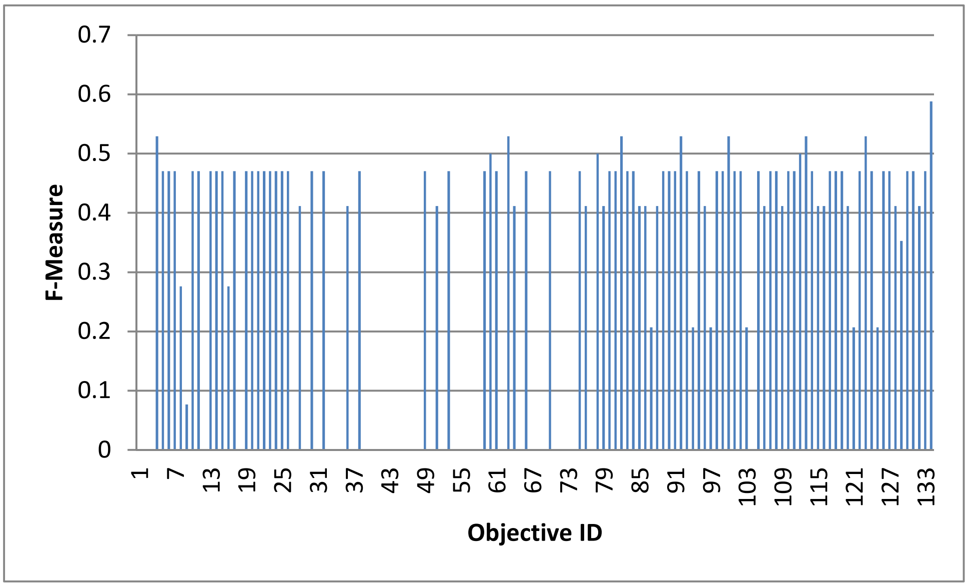

Figure 6.11: F-Measure Evaluation of Proposed Intelligent LOs Recommender

Table 6.12: Summary of the Main Statistical Measures of F-Measure

Min.	0	**Mean**	0.308731541
Max.	0.588235294	**Mode**	0.470588235
Variance	0.04558944	**Median**	0.441176471

6.5.3 Intelligent LOs Classifier Evaluation

Presented Intelligent LOs Classifier is evaluated to check its accuracy and capability to classify unclassified documents. Intelligent LOs Classifier implements Naïve-Bayes classifier algorithm. The following training set was given to the classifier. Table 6.13 presents categories and documents for each document that the classifier was trained on. Table 14 presents the results of testing. Testing set is presented to the trained classifier. Intelligent LOs Classifier resulted in 100% accuracy.

Table 6.13: Summary of Intelligent LOs Classifier Training Set

Category	Training Document
Bioinformatics	
	Biologically Inspired Computation
	Dynamical Systems in Neuroscience
	Molecular Analysis of Cancer
	Probabilistic Models of the Brain Perception and Neural Function
BPM	
	BPM Success: How a Travel Giant Turned its Ship Around CIO
Computer Networks	
	Interconnecting CISCO network devices Part 1
	Interconnecting CISCO network devices Part 2
	Portable Command Guide
e-Learning	
	101 free e-Learning tools
	Adaptive and Personal LMS

	E-Learning Technologies
	Questionmark-Tools-Effective-Assessments
	SCROM-v1
English	
	New interchange 1-key
	New interchange 1-student book
	New interchange 1-workbook
	Intro Workbook 3rd edition
Programming	
	ASPNet in VB
	ASPnet MVC
	Applied Numeric Methods using Matlab
	Essential Matbal for Engineers and Scientists
	Visual Basic 2008
SOA	
	SOA Description
	SOA Lab Setup Guide
	SOA Release Notes
	SOA Design Patterns
	SOA Instructor Exercises Guide
	SOA Lab Setup Guide Classroom
	SOA Lab Setup Guide Online
	SOA Student Exercises
	SOA Student Book

Table 6.14: Summary of Intelligent LOs Classifier Testing Set

Document	**e-learning by design**	
Class Percentage		
	English	NaN
	e-Learning	-17510.210584564997

	Bioinformatics	-20216.649226425725
	BPM	-17698.0930699629
	Computer Networks	-20366.694928274974
	SOA	-19893.456729741945
	Programming	-22055.679402138958
Decision	**e-Learning**	
Document	**effective e-Learning environment personalization using web usage mining technology**	
Class Percentage		
	English	NaN
	e-Learning	-21879.011486226136
	Bioinformatics	-25730.60082626081
	BPM	-25055.906020316877
	Computer Networks	-25432.70422899807
	SOA	-25199.419281366278
	Programming	-28851.363753332593
Decision	**e-Learning**	
Document	**CCNP2_SLM_v50**	
Class Percentage		
	English	NaN
	e-Learning	-769103.2978993196
	Bioinformatics	-839262.6497608843
	BPM	-695368.4959748124
	Computer Networks	-610877.2165053524
	SOA	-784774.4069853874
	Programming	-855032.0508602582
Decision	**Computer Networks**	
Document	**forrester_bpm_wave**	

Class Percentage		
	English	NaN
	e-Learning	-83003.91116782578
	Bioinformatics	-94739.36297244373
	BPM	-78479.22990639707
	Computer Networks	-89490.77817552155
	SOA	-84576.42321484128
	Programming	-101919.05505022638
Decision	**BPM**	
Document	**Network_Fundamentals_2D_IRG**	
Class Percentage		
	English	NaN
	e-Learning	-31300.31339492937
	Bioinformatics	-33352.432161580524
	BPM	-29577.875485405537
	Computer Networks	-29199.402824383295
	SOA	-32654.278796223974
	Programming	-36143.44494075163
Decision	**Computer Networks**	
Document	**Prentice.Hall.SOA.Principles.of.Service.Design.Jul.2007**	
Class Percentage		
	English	**NaN**
	e-Learning	**-810529.5972492553**
	Bioinformatics	**-991026.2503207972**
	BPM	**-962086.7346663276**
	Computer Networks	**-933969.3054615034**
	SOA	**-730561.9506475903**
	Programming	**-1049997.9439706628**
Decision	**SOA**	

6.6 Summary

This chapter presents the optimization activity we have been through this dissertation and highlights the optimization concepts have been focused on. Helping e-Learning in presenting new Adaptive e-Learning Models that enhances the e-Learning experience, presenting new Intelligent Services to provide advanced functionalities that cannot be achieved using standard methods, and enhancing the presented services are the activities that form the complete lifecycle of optimization. Optimization is an iterative and recursive operation that shall take place all the time, in order to enhance systems.

Optimized Solution shall be evaluated from different perspectives. To evaluate the Adaptive e-Learning Models, we surveyed the two target categories of the models: Students and Instructors. Both of them showed interest in the presented Adaptive e-Learning Models and feel that it can enhance the e-Learning experience greatly. Students have issues with the repeated exams process, and grouping students in smaller groups. However, they liked the adaptivity features presented. Instructors suspected the applicability of intelligent cheat depressor service, however they still agree to use it as an indicator, and the final decision remains their decision of course. The second perspective to evaluate the optimized Adaptive e-Learning Models and Intelligent Services from is Information Retrieval (IR). Information retrieval measures of proposed Intelligent LOs Recommender shows an achievement in precision measure, with challenges at Recall and F-Measure due to the increased number of relevant learning objects as a result of including the course objectives at the crawling phase. That means, almost all of the Learning Objects stored in the database is already relevant. Future work includes expanding the proposed Intelligent LOs Recommender automatic annotation of media LOs.

Finally, optimized Adaptive e-Learning Models and Intelligent Services evaluated another service that is: Intelligent LOs Classifier. Presented Intelligent LOs Classifier uses Naïve-Bayes Classifier, and it showed 100% classification capability.