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博 士 論 文

輔助超媒體科學學習環境中自我調適學習之適性化鷹架系統

A Novel Adaptive Scaffolding Scheme for Self-Regulated Science Learning in Hypermedia-based Learning Environments

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摘　　要

科學教育的目標是要建立學習者的科學知識架構與各種科學過程技能，而不同背景知識、不同學習風格的學習者常常需要不同的學習路徑來了解目標的知識與技能，超媒體學習環境能夠提供科學學習較好的學習成效，因為這種有彈性的學習環境能夠提供非線性的學習流程以符合不同的學習需求，學習者能夠選擇自己適合的路徑學習來學習目標概念，而多樣化的表現媒體也更適合展示各種過程技能的教學。然而，因為學習者缺乏自我調適學習的能力來決定自己的學習路徑與策略，非線性學習流程中大量的學習流程選擇也造成學習上的困難。

因此學習鷹架常常被使用來幫助低自我調適學習能力的學習者當這些學習者在學習中不知如何調適自己的學習。適性學習鷹架是不斷的觀察學生的學習狀況，並適時適性的給予學習輔助的方法，根據之前的研究，適性學習鷹架比固定型的學習鷹架更能增進學習成效，但是，提供適性學習鷹架將會造成老師沉重的教學負荷。雖然一些智慧型家教系統也能夠模擬老師的教學策略來提供適性學習鷹架自動幫助學習者，但要在非線性學習流程中使用這些既有的方法卻仍舊有困難，因為分歧的學習歷程與背景知識使得智慧型家教系統所要實作的老師教學策略必須比以往的線性流程還要複雜許多。

也因此產生了三個針對非線性學習流程建立學習鷹架而造成的子問題：描述非線性學習計畫、為多樣的學習者需求調適學習內容、由異質性的學習歷程診斷學習狀況。這篇論文提出一個新的適性化鷹架系統，其中擴展的狀態機模型、多顆粒粗細度的學習內容模型、以及以本體論為基礎的知識架構被設計來分別解決上述的三個子問題，論文中也提供了相對應的驗證結果與應用的實際案例。

A Novel Adaptive Scaffolding Scheme for Self-Regulated Science Learning in Hypermedia-based Learning Environments

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ABSTRACT

Science education aims to build learners' scientific knowledge structure and varied process skills. The scientific learners who have various prior knowledge and learning styles usually need various learning processes to master the concepts or skills. This learning requirement can be fulfilled by Hypermedia-based Learning Environments, where the free learning environments can provide a non-linear learning process for various learning needs. In the non-linear learning process, learners can freely select appropriate learning paths to achieve the learning goal and the diversified presentation can demonstrate varied process skills. However, the large number of learning choices provided by this kind of flexible learning environment usually make learning more difficult if learners lack self-regulated learning (SRL) abilities to decide their learning processes and strategies. Thus, scaffoldings, which suggest or guide learners when learners cannot self-regulate their learning, are usually used to help low-SRL-ability learners. According to previous researches, adaptive scaffoldings, which dynamically provide learners assistance according to learners' status, can improve learning performance and facilitate SRL behaviors better than fixed ones, but providing adaptive scaffoldings would cause heavy loads on teachers. Although some of existing Intelligent Tutoring System (ITS) approaches can provide adaptive scaffoldings, applying these approaches in the non-linear learning processes is still difficult. This is because the diverse portfolios and prior knowledge generated by various processes cause the teaching strategies more complex than ones for linear learning processes.

Thus, In this dissertation, three subproblems about representing non-linear learning plans, adapting learning content to diverse learners' requirements, and diagnosing learners' status by heterogeneous portfolios are defined. For solving these subproblems, a novel adaptive scaffolding scheme is proposed, where a generalized finite state machine, a multi-granularity learning content model, and an ontology-based knowledge structure are designed to solve the three subproblems, respectively. The evaluation results and the applying cases are also provided in this dissertation.

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List of Abbreviations

Abbreviation	Full Name
AC	Action Continuity
ADP	Adaptation Decision Process
AR	Assessment Rules
AS	Action Sequence
CADT	Content Adaptation Decision Tree
CAP	Content Adaptation Process
CM	Concept Map
CSP	Content Scaffoldings Provider
CVClustering	Content Version Clustering Algorithm
DNF	Disjunction Normal Form
DR	Diagnosis Rule
DRGalgo	Diagnostic Report Generation Algorithm
DT	Delivery Time
EO	Experiment Operation
GFSM	Generalized Finite State Machine
HANd	Hierarchical Atomic Navigation Concept
HKD	Heterogeneous Knowledge Diagnosis model
HLE	Hypermedia-based Learning Environment
ID3	Iterative Dichotomiser 3
ISODATA	Iterative Self-Organizing Data Analysis Technique algorithm
ITS	Intelligent Tutoring System
IRT	Item Response Theory
KA	Key Action
KOAP	Key Operation Action Pattern
LAMS	Learning Activity Management System
LCI	Learning Caution Indexes
LCS	Learning Content Synthesizer
LMS	Learning Management System
LOR	Learning Object Repository
MGC	Multi-Granularity Content model
NORM	New Object oriented Rule Model
OAPDP	Online Assessment Portfolio Diagnosis Process
OC	Object Continuity
OOLA	Object-Oriented Learning Activity System
OPASS	Online Portfolio Assessment and Diagnosis Scheme
PLCAM	Personalized Learning Content Adaptation Model
PPFO	Preferred Picture Format Ordering
PSP	Plan Scaffolding Provider
SCORM	Sharable Content Object Reference Model
SM	Skill Map
SRL	Self-Regulated Learning
SSP	Suggestion Scaffolding Provider
SWV	Satisfaction Weight Vector
TIPS	Test of Integrated Science Process Skill

List of Symbols

Symbol	Description	Chapters
s_i	A state, denoting a suggested learning activity	Chapter 3 and 4
μ_k	A learner model	Chapter 3
Σ	A set of inputs, denoting learner models	Chapters 3, 4, 5, and 6
S	A set of states, which represent learning activities	Chapters 3 and 4
c_j	Contents	Chapter 3
C	A set of contents	Chapter 3
e_l	A learning event	Chapters 3 and 6
s_0	The initial state	Chapter 4
δ	A transition function	Chapter 4
F	A set of final states	Chapter 4
a_{ij}	An attribute	Chapter 4
N	The number of attributes in μ_k	Chapter 4
f_{now}	A fact of current state	Chapter 4
f_{next}	A fact of next state	Chapter 4
f_{ai}	A fact of attribute a_i	Chapter 4
N_{LA}	A set of states denoting lecturing activities	Chapter 4
N_{AP}	A set of states denoting education applications	Chapter 4
N_{EA}	A set of states denoting examination activities	Chapter 4
F	A set of possible feature sets	Chapter 5
N	A set of nodes of all granularities in cases	Chapter 5
n_i	A node of a content version	Chapter 5
F_i	A set of features	Chapter 5
$child_i$	A set of children nodes	Chapter 5
$level_i$	The level of granularity	Chapter 5
$content_i$	The original content of the version n_i	Chapter 5
SF	A satisfaction function	Chapter 5
$\Re$	The degree of the adaptation quality	Chapter 5
CP_i	A set of concept properties	Chapter 5
HP_i	A set of hardware properties	Chapter 5
LP_i	A set of learner properties	Chapter 5
MP_i	The media parameters	Chapter 5
type_i	The media type	Chapter 5
$size_i$	The size of this media version	Chapter 5
WV	A *Weight Vector*	Chapter 5
w_k	A weight in a weight vector	Chapter 5
E	The Entropy	Chapter 5
I	The information gain	Chapter 5
MP_{set}	A set of media parameters	Chapter 5
$T_{expected}$	The average expected time of deivering each requested media-level nodes	Chapter 5
T_{used}	The actual deliver time	Chapter 5
MP_{candi}	The candidate *MP* list	Chapter 5
$Media_{req}$	The set of requested media-level contents	Chapter 5

$T_{transcoding}$	The estimated transcoding time	Chapter 5
T_{MDT}	The maximum available delivery time	Chapter 5
$T_{deliver}$	The estimated deliver time of the n_i	Chapter 5
c_i	A concept	Chapter 6
Ontology	A set of ontology	Chapter 6
F	A set of frames	Chapter 6
f_i	A frame of learning activity	Chapter 6
E_i	A set of all learning events	Chapter 6
V_i	A set of all slot values	Chapter 6
CR_i	The learning status crystalization rule set	Chapter 6
P	The set of predicates of learning status	Chapter 6
DR	The diagnostic rule set	Chapter 6
CM	A concept map	Chapter 6
C	A set of concepts	Chapter 6
c_i	A concept	Chapter 6
R	A set of relations	Chapter 6
cr_i	A concept relation	Chapter 6
SM	A skill map	Chapter 6
S	A set of skills	Chapter 6
s_1	A skill	Chapter 6
sr_1	A skill relation	Chapter 6
EO	All actions that a learner can operate	Chapter 6
a_1	An action	Chapter 6
Ar_i	An assessment rule	Chapter 6
Cs_i	A condition setting	Chapter 6
Step_i	The name of an experiment step in the scientific inquiry assessment experiment	Chapter 6
$\mathrm{Problem}_\mathrm{i}$	A checking predicate function of Step_i	Chapter 6
Dr_1	A diagnosis rule	Chapter 6

Chapter 1 Introduction

In science education, learners are asked to have deep understanding and master scientific inquiry skills in science domain [33]. Thus, many kinds of scientific inquiry assessment [34, 101, 102] and learning activities [77] are used to assist learners in understanding the complex knowledge structure and varied process skills. In addition to traditional face-to-face learning activities, Hypermedia-based Learning Environments (HLE) are also used widely to support science education to enhance learning efficacy and balance teachers' loading [58, 71]. The hypermedia-based learning environments are suitable to the science learning [51] because the free learning environments can provide non-linear learning processes, which can facilitate learners to construct knowledge structures on the basis of their own prior knowledge, and the diversified presentation are suitable to demonstrate varied process skills. However, without any support, most of the learners cannot obtain high learning performances due to the lack of self-regulated learning (SRL) abilities [36, 79], including planning goals, controlling strategies, monitoring performance, and reflecting on status [72]. SRL scaffoldings, which suggest or guide learners to regulate their learning when learners lack abilities to do the SRL well, are widely used to help learners learn in HLE [7].

SRL Scaffoldings are usually categorized into fixed scaffoldings, which are the same documents or suggestions for all learners, and adaptive scaffoldings, which can provide suggestions according to learners' learning status [5]. Azevedo and his colleague [6] apply fixed scaffoldings, adaptive scaffoldings, and no scaffoldings in learners' learning process to evaluate how various scaffoldings can affect learners' understanding of topics and SRL behaviors. In this research, the fixed scaffolding was a list of questions to remind learners to self-regulate their learning, and the adaptive scaffolding was suggestions provided by teachers according to learners' status when learners cannot regulate their learning well. The experimental results of this research showed that adaptive scaffoldings based on ongoing learning diagnosis can significantly improve learners' self-regulation and learning performances. However, in the real learning situation, it is costly for teachers to take care of all learners to provide adaptive scaffoldings. Thus, this dissertation aims to propose a Novel Adaptive Scaffolding Scheme, which can adopt teachers' expertise, to provide adaptive suggestions to help learners regulate their learning in the hypermedia-based learning environment. The main difficulty toward this goal is how to adopt teachers' expertise by using Information Technology (IT) to provide appropriate scaffoldings.

The mechanisms used in the IT domain to adopt teachers' knowledge in a system, called Intelligent Tutoring System (ITS), can be categorized into the conventional-program-based approach and the knowledge-based approach. The former uses hard-coded algorithm to simulate teachers' teaching strategies. However, as an ITS is used wider and wider, more teaching strategies are required to be applied to satisfy various learners' needs. The teaching strategies embedded in the algorithms are difficult to be maintained and acquired, so the cost of refining and maintaining algorithm would grow rapidly. The latter separates the domain expertise, represented by knowledge models, from the inference logics, so the teachers' knowledge can be refined easily without changing program codes. The knowledge model, explicitly representing teachers' teaching strategies, can also facilitate to maintain and acquire teachers' knowledge. However, the variety of learners' portfolios and requirements in the non-linear learning processes of HLE makes the adopted teaching strategies complex, so the major challenge to apply knowledge-based approaches is how to design a suitable knowledge model to satisfy the teaching requirements of the non-linear learning processes provided by the free HLE. This dissertation defines and solves three subproblems caused by providing adaptive scaffoldings in the non-linear learning processes, where three knowledge models are proposed in the Novel Adaptive Scaffolding Scheme to solve the three subproblems, respectively. The subprobems, the related ITS mechanisms, and the proposed ideas are listed as follows.

Learning Process Representation Subproblem

The learning process in HLE is non-linear, which usually makes learners difficult to plan their learning goals, because these learners cannot choose the most suitable learning paths to their learning status among the large amount of choices. Thus, in order to suggest learners appropriate learning paths, teachers' typical learning paths for various kinds of learners and rules of selecting learning paths need to be adopted in the adaptive scaffolding scheme.

Existing ITS mechanisms which provide adaptive navigation support [2, 14, 18, 20, 44, 78, 91] can facilitate teachers to generate typical learning plans and suggest learners with the appropriate learning paths. However, for the non-linear learning processes, the typical learning plans need to be complex with many candidate learning paths, and this kind of mechanisms still lack the knowledge model which can fulfill both expressive power and understandability. A Learning Process Representation Subproblem occurs where a knowledge model needs to be designed to satisfy both adequate expressive power to represent teachers' learning path selection knowledge and good understandability for teachers to provide their expertise.

In order to solve the Learning Process Representation Subproblem, the proposed scheme generalize a finite state machine, which is an easy-to-understand model to represent conditional processes, to represent the learning processes. The new model proposed in this dissertation is named **Generalized Finite State Machine**, where the states denote learning activities and the extended transition functions express the complex teaching strategies of learning path selection.

Personalized Content Adaptation Subproblem

In the non-linear learning processes in the free HLE, learners have diversified learning progress and even various learning environments and meida. Choosing appropriate content to satisfy learning requirements is a key task of controlling learning for a learner. However, the diverse requirements need to be satisfied by providing huge number of versions for each content, and it is difficult for learners to find appropriate versions by themselves.

Learning recommender mechanisms in ITS [29, 46, 54, 65, 66] can recommend existing learning materials to learners according to learning styles, prior knowledge, and environments, but the huge number of content is needed for the learners' diversified needs. Content Adaptation mechanisms [11, 15, 30, 53, 57, 75, 97, 99] can dymanically generate new content for learners' requirements by fragmenting and recombining original content. However, managing large number of content fragments to efficiently provide learners appropriate content is still difficult, which is called a Personalized Content Adaptation Subproblem.

In order to solve the Personalized Content Adaptation Subproblem, the original content is decomposed into blocks with the inner media and text. Various versions of content can be generated for various requirements by transcoding some media. A **Multi-Granularity Content model** is proposed to manage these versions of content, where a version is represented as three granularities: page level, block level, and media level. When a request is received, the system can retrieve the most suitable version of the page firstly to find the more or less suitable content version and adapt it to the detailed requirements by replacing the blocks from other versions and transcoding the media if the request time is acceptable. Thus, the content adaptation process from coarse-grained to fine-grained can efficiently retrieve good-enough content and effectively refine it to the suitable content.

Process Skill Diagnosis Subproblem

In addition to the traditional lectures and examinations, an HLE can provide varied learning media and activities, such as virtual laboratories, to enhance the effectiveness of science learning. These activities can generate various learner portfolios to record learners' behavior and performances for monitoring and reflecting on their learning status. However, the various learning paths and diverse learner portfolios in the non-linear learning processes make moitoring and reflecting difficult because learners are difficult to refer to peers' performances and progress.

Existing learning diagnosis mechanisms [17, 38, 45, 56, 62] in ITS domain can effectively diagnose learners' performance by traditional assessment results, but the ideas of these mechanisms are difficult to be applied to diagnose scientific process skills and learning behaviors for the science learning because heterogenerous learner portfolios generated by the scientific learning activities cannot be analyzed by the existing appraoches. Thus, a Process Skill Diagnosis Subproblem is defined as how to manage and organize the heterogenerous learner portfolios and provide learning diagnosis by applying the teaching expertise to these diversified portfolios to assist learners in monitoring and reflecting on learning status.

For the Process Skill Diagnosis Subproblem, because the heterogeneous learner portfolios are difficult to be analyzed and used in learning diagnosis, a **Heterogeneous**

Knowledge Diagnosis model is proposed where the learners' behaviors in science learning activities can be identified as correct or incorrect actions by using the proposed key operation action patterns. These heterogeneous learning events are organized into an ontology-based knowledge structure, which is a tree of concepts and process skills with the relations connecting among the nodes. With the relations of concepts and process skills, it is easy to find the causal relationships between events and learning performances. Thus, the high-level learning diagnosis knowledge is easy to be applied to the organized portfolios.

Generally speaking, this dissertation proposes a novel adaptive scaffolding scheme to assist learners in self-regulating their learning in the scientific learning domain. This knowledge-based scheme applies teachers' educational knowledge to diagnose learners' learning status and provide scaffoldings to fit individual learners' needs. In order to evaluate the effectiveness of the proposed novel adaptive scaffolding scheme, three sub-systems based upon the three proposed models, including a Generalized Finite State Machine, a Multi-Granularity Content model, and a Heterogeneous Knowledge Diagnosis model, were constructed and the corresponding experiments were conducted. The results show that the adaptive scaffoldings for planning learning based on Generalized Finite State Machine can significantly improve low-grade learners' learning performances. For supporting learning content selection and adaptation, the proposed Multi-Granularity Content model is more efficient than the previous approaches to provide more appropriate content. For monitoring and reflecting on learners learning status, the scaffoldings based on the Heterogeneous Knowledge Diagnosis model can also improve learners' motivation to understand learning problems.

In the rest of the dissertation, the related works about Self Regulated Learning scaffolding systems and the issues raised for non-linear scientific learning processes are introduced in Chapter 2. In order to overcome these issues, a Novel Adaptive Scaffolding scheme is proposed and described in Chapter 3, where three subproblems about non-linear scientific learning processes and the corresponding models used to solve the problems are introduced. In Chapters 4, 5, and 6, the three models and their evaluation are detailedly described, respectively. Afterward, a conclusion and the references used in this dissertation are provided in Chapters 7 and 8, respectively. Finally, the cases of applying the proposed models to real learning situations are given in appendices.

Chapter 2 Preliminaries

The free learning processes and varied presentation can satisfy more requirements of learners to learn scientific concepts and scientific inquiry capabilities, but the learners' performance might become low because the learners cannot make decisions among the large number of choices in the flexible learning environment without enough ability of SRL. Thus, scaffoldings are necessary to help these learners regulate their learning. In this chapter, the scientific inquiry and process skills are described firstly, and SRL models and the existing scaffolding approaches are also introduced.

2.1 Scientific Inquiry and Scientific Process Skill

Today, Scientific Inquiry-based learning receives widespread attention. The purpose of such learning is to promote students' knowledge and understanding of scientific ideas as well as how scientists study the natural world [19]. If students possess scientific inquiry skills, they are capable of conducting an investigation, collecting evidence from a variety of sources, developing an explanation from the data, and communicating and defending their conclusions [35]. Scientific inquiry can be considered as a set of process skills that consists of questioning, hypothesis-making, experimenting, recording, analyzing, and concluding, which can be regarded as "hands-on" learning [19, 52]. The knowledge and capabilities of scientific inquiry are multidimensional [19, 34, 92] and can be divided into three types: (1) Substantive Knowledge, e.g., scientific concepts, facts, and processes; (2) Procedural Knowledge, e.g., procedural aspects of conducting a scientific inquiry; and (3) Problem Solving and Integrative Abilities, e.g., the ability to solve problems, pose solutions, conceptualize results, and reach conclusions [50].

2.2 Self-Regulated Learning and Its Scaffolding Survey

Self-regulation is a learning skill employed to actively construct knowledge. Pintrich [72] defined self-regulation as the planning, monitoring, controlling, and reflecting phases. The behaviors of cognition in each phase are described as follows:

- **The Planning Phase**: A learner activates prior knowledge and plans learning goals and processes.
- **The Monitoring Phase**: A learner monitors what he/she has learned and evaluates the learning performance toward the goals.
- **The Controlling Phase**: A learner controls and adjust learning strategies and materials to achieve the learning goals.
- **The Reflecting Phase**: A learner reflects on and refines the learning strategies and processes to continuously improve the learning effectiveness.

Besides, other researchers also define various models of SRL to describe a learner's cognitive process. Winne and Hadwin [94] posited that learning happened in four phases: task definition, the goal setting and planning, the studying tactics, and adaptation to metacognition. Zimmerman [103] defined that the SRL includes three main phases: the forethought phase, including task analysis and self-motivation beliefs, the performance phase, including self-control and self-observation, and the self-reflection phase, including self-judgement and self-reaction. Although the definitions of all researchers' models are different, the described learning actions in all models are similar and can be mapped to Pintrich's model in general. For example, the task definition, the goal setting and planning phases in the Winne and Hadwin's model can be regarded as the planning phase in Pintrich's model; the studying tactics can be mapped to the control phase; and the adaptation to metacognition phase can be considered as the monitoring and reflecting phases in Pintrich's model.

Thus, this dissertation uses SRL scheme mainly based upon Pintrich's SRL model to define what scaffoldings should be provided by teachers while learners cannot successfully complete the tasks of their self-regulation:

- In the **planning** phase, learners plan their learning activities, so teachers need to suggest learners who cannot plan their own learning with typical learning plans.
- In the **monitoring** phase, learners evaluate their learning performances, so teachers need to assist learners in evaluating their knowledge and skills.
- In the **controlling** phase, learners control learning strategy and the presentation of materials, so teachers have to assist learners in determining which content and presentation is appropriate and adapt the content presentation for learners' needs.
- In the **reflecting** phase, learners should reflect on learning status and find out themselves' learning barriers, so a learning diagnosis is usually needed to determine how to remedy the learners' learning barriers.

Azevedo [6] categorized scaffoldings into fixed and adaptive scaffoldings. Several **fixed scaffolding systems** were proposed in recent years to help learners be aware of each phase of self-regulated learning.

- Abrami [1] proposed an E-portfolio system to assist learners in planning their learning, where learners could create learning works, set learning goals, upload learning results, and share these plans and results to teachers, peers, and parents.
- In order to teach learners to plan their learning and problem solving activities, Ge [28] provided learners prompts of five problem solving steps in a problem-based learning activity.
- Shih [80] developed a platform to facilitate learners to plan and monitor their learning schedules, where learners could customize their own learning schedules based on teacher-provided schedule templates and monitor learning time, attempts, and progress.
- KnowledgePuzzle [3] can facilitate learners to mark the segments in hypertext content and

define relations bwtween these segments to plan the navigation path. The tool can also regenerate the hypertext by integrating the segments according to the navigation plan to facilitate to read.

- Siadaty and her colleaegues [82] use competence ontology to model a company's necessary skills and provide workers suggestions of learning goal planning and tools to monitor workers' learning status.

According to previous evaluation, the fixed scaffoldings can make learners be aware of planning and monitoring their learning, but these scaffoldings lack personalized support to address learners’ indivudual learning needs [6]. Adaptive scaffoldings were provided to help learners overcome their barriers of SRL according to learners' status. In the research [6], adaptive scaffoldings provided by teachers can offer learners better learning effectiveness, but the wide use of this kind of adaptive scaffoldings in the real learning environments would cause heavy loads on teachers. ITS mechanisms, aiming to use IT mechanisms to guide learners to learn and overcome their learning barriers, could be solutions to widely provide adaptive scaffoldings without much increase teachers' loads.

ITS approaches can be categorized into conventional-problem-based approachs and knowledge-based approaches. The former develop intelligent logics by hard-coded programs, and the latter aims to seperate the teaching knowledge from system control logics. The following sections introduce these two kinds of intelligent tutoring system approaches.

2.3 Intelligent Tutoring System Approach Survey

Many existing intelligent tutoring systems were designed by conventional programs, where the teachers’ teaching strategies are simulated by using artificial intelligent algorithms.

Planning Support

Some existing learning systems, providing adaptive navigation support to guide learners learning, can assist learners in planning their learning.

- Iglesias [49], Su [84] and their colleagues provided learners adaptive learning sequences according to learners' learning performances and prior knowledge by using reinforcement learning and planning algorithm, respectively.
- Hsiao and her colleagues [42] proposed parameterized questions, having attributes such as difficulty and concepts, and applied adaptive navigation support to select questions for learners to enhance learning effect and motivation.
- Context-dependent parameters [16] and learning styles, such as Field Independent/Field Dependent, visual/verbal, abstract/concrete, etc. [73], were also used to compute the adaptive learning sequences.
- Hwang [48] proposed an adaptive game-based learning system where the learning styles, global/sequential, are used to determine the game sequence.
- Flores [24] grouped learners by using high/low prior knowledge and high/low motivation, and provide adaptive tutorials by using the groups.
- Shih and her colleagues [81] used online-test to diagnose learners' abilities of concepts and gave adaptive remedial instrucction according to the concept abilities.
- Despotović-Zrakić [21] clustered learners by learning styles, such as active/reflexive, sensitive/intuitive, visual/verbal, and sequential/global, and provided adaptive course to each cluster.
- Huang and his colleagues [43] used sequential pattern mining to find recommended concept-learning path. In order to provide adaptive presentation, the user-voting approach and Item Response Theory (IRT) were used to determine the learners' ability levels and learning objects' difficulty levels.

Monitoring and Reflecting Support

For helping learners monitor and reflect on their learning processes in the science education, there were plenty of customized virtual laboratories [23, 41, 52, 93, 100] that constructed environments of specific experiments for scientific inquiry to assess learners' integrated abilities including scientific knowledge and process skills, but constructing a hard-coding virtual experimental environment for each specific experiment was costly and time consuming.

The learning diagnosis mechanisms were defined to assist learners in reflecting on their learning status and finding their learning barriers.

- Liu and Yu [64] proposed an Aberrant Learning Detection approach, which finds learners who have low learning performances due to non-cognitive factors by using Learning Caution Indexes (LCI) to detect the difference between the real learning performance and the estimated performance from Item Response Theory (IRT).
- Moridis and his colleague [69] constructed an affect recognition system by formula-based method and Artificial Neural Network (ANN) method to predict learners' mood in online self-assessment and give affective feedbacks after or before assessment.
- Gonzalez and his colleagues [31] proposed a math problem diagnosis system, where mistakes in Math solutions are matched by predefined mistake patterns and provide corresponding remedial action suggestions.
- Wu [95] proposed an intelligent tutee system to encourage learners learning by teaching in a concept mapping activity. The adaptive prompts are used to elicit learners' reflection on cognition and meta-cognition.
- Barnes and Stamper [8] proposed an automatic hints generator for logic proof by Markov

decision processes, which are constructed using previous learners' solution.

These conventional-program-based intelligent tutoring system approaches could provide learners effective assistance in parts of self-regulated learning processes. However, the teaching environments and subjects are continuously changing, but the teaching knowledge embedded in the systems is difficult to be acquired and maintained. Thus, the requirements of knowledge-based approaches appear to provide learners learning systems having higher maintainability. The following subsections introduce the existing knowledge-based ITS mechanisms, which can support learners to plan, control, monitor and reflect on their learning.

2.3.1 Knowledge-based Learning Planning Support Mechanism

In order to provide learners adaptive learning paths to help plan their learning, some editable adaptive navigation support mechanisms and specifications were proposed.

- SCORM Sequencing and Navigation [2] is one of the most popular adaptive learning activity specifications, where teachers can represent their learning strategies as the sequencing rules to control the learners' learning paths among the learning materials.
- Sakurai and his colleagues [78] proposed a dynamic storyboarding to manage didactic knowledge, representing learning sequence templates, and assist learners in planning university subjects. The results showed the system was beneficial for learning.
- Clemente, Ramírez and Antonio [18] proposed a rule-based learning diagnosis, which can find appropriate learning materials according to learning objectives, learners' abilities, and materials' topics.

Although teachers can represent their teaching strategies as rules by using these approaches, for teachers to take care of the detailed inference of adaptive learning rules is still difficult. Thus, graph-based models were proposed to enhance the understandability of learning processes by visualizing the designed processes.

- LAMS [20] is a user-friendly learning activity planning system, where teachers can design a collaborative learning process for the whole class, but the linear learning process designed by LAMS cannot represent adaptive learning strategies for personalized learning.
- The dynamic fuzzy Petri Nets (DFPN) [14, 44, 91] was used to represent the behavior of tutoring agent, where the learning activity contains a main learning sequence. After a post test, the remedial learning contents can be shown if the score of test is lower than the threshold.
- Inference diagrams [12, 61] were also used to describe the courseware diagram and support the evaluation of learners' learning performance. The learning sequence of each learner can be various with different score range after an examination. Similar to the researches of DFPN, adaptive navigation support is only based on single test score and cannot express the learners' complete learning statuses.

These models can provide adaptive navigation support according to the single test score, but the lack of expressive power make it still difficult to express teaching strategies for complex learning portfolios. Thus, how to facilitate teachers to intuitively design the adaptive learning plan to support learners in planning their learning processes is a critical issue.

2.3.2 Knowledge-based Strategy Control Support Mechanism

For supporting learning strategy control, most of existing approaches focus on content selection and adaptation. Learners having various styles, prior knowledge, learning paths, and learning devices require personalized content presentation to satisfy their learning needs. When learners control their learning, selecting an appropriate learning content is necessary to ensure learning effectiveness. Thus, some learning content recommenders were proposed to assist learners in choosing existing learning content in the repository.

- Graf and her colleagues [32] proposed a tool DeLeS, which can automatically detect learners' learning styles in LMS for teachers to understand their learners. Learning styles include attempts of learning, preference of content types and learning types, and navigation styles.

- Mampadi and his colleagues [65] proposed an adaptive navigation support system to recommend learning materials according to the learners' learning styles, which emphasize on Pask's Holist-Serialist dimension.
- Manouselis and his colleagues [66] proposed a collaborative filtering recommender for learning resource, where teachers used multi-attributes ratings to parameterize resources and shared with others. Ghauth and Abdullah [29] also proposed a learning material recommender by incorporating keyword-based content-based filtering and average good-learner ratings.
- Klasnja-Milicevic, Vesin, Ivanovic and Budimac [54] proposed a recommender to recommend learning materials by clustering learners according to learning styles and finding habits and interests using frequent sequences mining.
- For the ubiquitous learning, Hwang and Chang [46] proposed a mobile learning approach which provides location-based formative assessment to encourage learners to observe the real environment and find the answers.

However, because of various learners' styles, prior knowledge, and learning devices, the number of learners' requirement combination can be large. The mechanisms mentioned above can only select existing content for learners, so the huge number of content versions, which should be prepared, cause the content version management and large search space problem. To cope with this problem, content adaptation mechanisms were proposed to adapt single content to satisfy wide range of requirements.

Fudzee and Abawajy [25] grouped content adaptation approaches into two basic types:

static adaptation and dynamic adaptation. The former usually generates multiple variants for each content component, attaching a layout description for the presentation of component-based Web content [40, 68, 89]. These static adaptation approaches can reduce download time, but they require preprocessing tasks and greater storage allocation. Another limitation is that they do not take into account the user's preference and the situation of the wireless network.

Many dynamic adaptation approaches, including content structure analysis and context-based adaptations, have been proposed to resolve these issues [25].

- A Hierarchical Atomic Navigation Concept (HANd) was proposed by González-Castaño and his colleagues [30] to navigate on small-scale devices, using the content structure analysis approach. In the HANd approach, an automatically generated navigator page is used to indicate some or all elements embedded in a World Wide Web (WWW) page. To generate the navigator page, a Web page is analyzed and fragmented into several separate "clipped" versions with the degrees of importance. According to the ability of the browsing device, the navigator page can determine a threshold of importance degree to control the amount of elements delivered to users.
- Based on a similar concept, many fragmentation and summarization processes have been proposed to organize a Web page into a thumbnail representation that indexes detailed information [15], breaks each Web page into several text units [11], and detects the important parts [99] or the interesting fragments in dynamic Web pages [75], thus reducing delivery latency.

However, not all Web pages are suitable for text summarization because summarized statements, as lossy information, may mislead users. To help improve understanding, the semantically coherent perceivable units of the Web content can be extracted and presented together on a mobile device according to their semantic relationships [53, 57, 97].

However, most of the aforementioned content adaptation approaches need to manage large number of content fragments, and face a combination explosion problem when the number of requirements become large. Thus, how to manage the content versions to facilitate personalized content adaptation still needs to be solved.

2.3.3 Knowledge-based Learning Diagnosis Support Mechanism

Learners in the non-linear science learning process require to monitor and reflect on their learning status of scientific concepts and process skills during the learning activities, including lectures, traditional examinations, and process skill learning activities, such as virtual labortory assessment. Existing learning diagnostic mechanisms can evaluate learners' learning status and provide remedial learning suggestions according to their test results.

- Lin and her colleagues [62] used item-concept relations and learners' correctness of items to calculate the learners' learning performances of concepts.
- Furthermore, Hwang [45] and Heh [38] proposed mechanisms which can determine remedial learning paths by referring learners' learning performances and the knowledge structure representing as a concept ontology. Hwang [47] further proposed a group decision approach which can integrate multiple experts' knowledge structures by using the rules-based approach. The integrated knowledge structure could be also used to diagnose learners' weak concepts and suggest remedial learning paths.
- Afterward, Chu, Hwang and Huang [17] proposed an Enhanced Concept Effect Relationship to represent concepts and their difficulty levels to improve the effectiveness of learning diagnosis.

Although these approaches can effectively provide diagnosis for traditional examination results, the lack of considering learners' learning behaviors in other kinds of learning activities causes the limitation of finding learners' barriers, especially for process skills learning.

- Kosba and his colleagues [56] proposed a mechanism, which can automatically generate adaptive feedback for teachers and learners according to the collected learning performances and learning behaviors by modeling teachers' high-level diagnostic knowledge using a rule-based approach.
- Mitrovic [67] proposed a constraint-based intelligent tutoring system, where the key action patterns are modeled as rules associated with the positive feedbacks. The system could give positive feedbacks when learners' actions are correct and uncertain.

However, the considered learning behaviors belong to traditional learning situations. The approache is still difficult to be applied to diagnose learners' scientific process skill learning.

In addition to the traditional assessments, in order to facilitate learners to evaluate their process skills, some editable virtual lab systems were also proposed for teachers to design scientific inquiry experimental tests.

- Higgins and his colleagues [39] proposed an authoring tool for teachers to construct diagram-based free-response assessment in electronics like logic circuit design. While teachers design the question, they can also set the marking file which is used to input their system for scoring of learners' answer. The teacher can use this authoring tool to create different diagram-based assessment in electronics.
- Yaron and his colleagues [98] proposed an authoring tool to provide teacher the flexibility of adding new chemicals and chemical equations. Learners can operate predefined

devices to conduct a chemical experiment, doing actions like mix chemicals or heat device to observe the reaction.

These mechanisms can provide virtual environments for learners to train their process skills, but the learning diangostic mechanisms were still lacked for evaluating learners' learning behaviors in the virtual experiments.

Current learning diagnostic mechanism can deal with the traditional learning situations well, and the high-level diagnostic knoweldge can also be modeled by using rule-based approaches in previous researches. However, for scientific learning, heterogeneous learning behaviors from process skill training and scientific concept learning are still difficult to be analyzed and applied by teachers' high-level diagnostic knowledge.

Chapter 3 Novel Adaptive Scaffolding Scheme

According to the analysis in the Chapter 2, although the previous studies have proven that the existing ITS approaches can facilitate teachers and learners to teach and learn effectively in specific domain and learning situations, scaffolding learners for each SRL phases among the non-linear scientific learning processes still causes some probems, as shown in Figure 3.1:

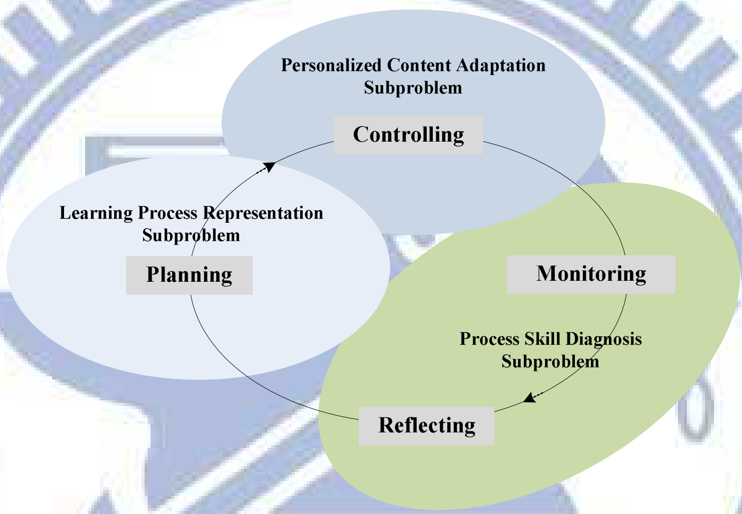


Figure 3.1: Subproblems and related SRL phases

Learning Process Representation Subproblem: Because of the lack of the appropriate learning process representation, teachers are difficult to design the adaptive learning plan to support learners in their planning phase.

Personalized Content Adaptation Subproblem: Due to the lack of content versions management approaches, efficiently providing personalized content adaptation to support learners in their controlling phase is difficult.

Process Skill Diagnosis Subproblem: Because of the heterogeneous learning behaviors from process skill training and scientific concept learning, analyzing learners' learning portfolios and applying teachers' high-level diagnostic knowledge to give learning diagnosis to support learners in their monitoring and reflecting phases is difficult.

To cope with these problems, a Novel Adaptive Scaffolding Scheme, including the Generalized Finite State Machine, the Multi-Granularity Content model, and the Heterogeneous Knowledge Diagnosis, is proposed. As shown in Figure 3.2, the Novel Adaptive Scaffolding Scheme includes three scaffolding providers to support learners to self-regulate their learning:

Plan Scaffolding Provider (*PSP*): A *PSP*, based on Generalized Finite State Machines to solve the Learning Process Representation Subproblem, can provide suggested learning plans to facilitate learners to plan their learning.

Content Scaffoldings Provider (*CSP*): When learners aim to control their learning materials, a *CSP*, based on a Multi-Granularity Content Model to solve the Personalized Content Adaptation Subproblem, can manage content versions and adapt learning content to the learners' requirements.

Suggestion Scaffolding Provider (*SSP*): During the learning process, learners need to monitor and reflect on their learning. A *SSP*, based on a Heterogeneous Knowledge Diagnosis Model to solve the Process Skill Diagnosis Subproblem, can give learning diagnosis and remedial suggestion to help the learners understand their own learning status.

All learners' learning portfolios, including records of reading content, test results, and portfolios of process skill training are stored into a **Learner Portfolio Database**. Learning resources, such as learning content and test items, are stored in the **Learning Content Repository** and **Test Item Repository**, respectively. Besides, learning applications, such as virtual laboratories, are stored into a **Learning Application Repository**. These learning portfolios and resources are refered and fired by the three scaffolding providers to provide learning scaffolding services.

In the beginning of learning, *PSP* can suggest next learning activities to help a learner plan learning processes according to the learning portfolios when planning learning processes. Afterward, in the controlling phase, the learner aims to learn with a learning content, *CSP* can provide an appropriate learning content according to the learner's portfolio and the planned learning activity. After learning and testing, *SSP* can support the learner to monitor and reflect on their learning status according to the learning portfolios and provide diagnostic report for the learner to plan the next round of learning. Thus, in the proposed scheme, the interoperability of all scaffolding providers is concerned to scaffold the learner's whole learning process.

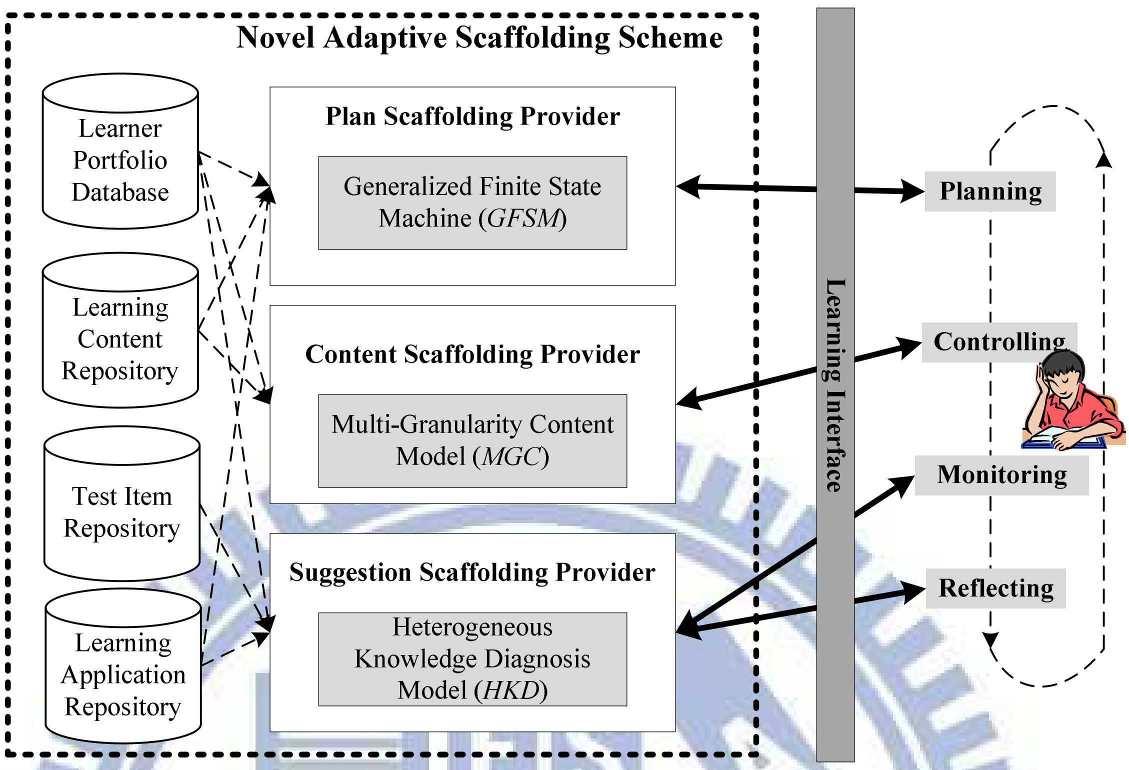


Figure 3.2: Novel Adaptive Scaffolding Scheme Architecture

3.1 Learning Process Representation Subproblem

In a non-linear learning process, three kinds of necessary elements should be represented in the learning activity plan: learning paths, learning activities, and the learning-path-selecting strategies. Various learning paths should be designed for various kinds of learners. Among the learning paths, learning activities, such as examinations, lectures, or projects, should be determined. Besides, in the branches of the learning process, the learning-path-selecting strategies based on teachers' teaching knowledge should be designed to guide learners to select appropriate learning processes. However, designing a model for teachers to design processes and learning-path-selecting strategies flexibly and easily is difficult.

Thus, the **Learning Process Representation Subproblem** is defined as *how to design a learning plan model, such that*

- *the model can represent the learning paths and learning activities,*
- *the model can represent learning-path-selecting strategies and these strategies can be*

executed to conduct learning planning, and

- *the model is easy to understand and be used to design processes for teachers?*

In order to intuitively represent the non-linear learning process to solve this Learning Process Representation Subproblem, a generalized finite state machine is used to model the knowledge of learning activity plans. The Generalized Finite State Machine (GFSM) is designed by generalizing a traditional finite state machine, where a compound input is used to represent multiple attributes of a learner's status and the rules of the Disjunction Normal Form (DNF) are used in the new transition function to express the teachers' learning-path-selecting strategies.

3.2 Personalized Content Adaptation Subproblem

In order to fulfill individual learners' learning styles and learning status, the presentation of a learning material should be various. Existing content adaptation mechanisms can adapt the text or multimedia items to various presentation needs, but how to manage and reuse the adapted presentation versions to efficiently provide learning content is still an important issue. The existing learning content recommender systems consider a learning material as a static item. If a huge number of presentation versions are adapted for various requirements, the recommender should manage all the versions and have large search space for recommending a material for a new learner. If all the materials are stored as the detailed chunks of all adapted versions, the recommendation is still inefficient due to the combination explosion of these chunks for forming a complete learning material.

Thus, the **Personalized Content Adaptation Subproblem** is defined as *how to control the granularity of the stored content presentation versions, such that*

- *the response time of the mechanism is acceptable, and*

- *the mechanism can retrieve or adapt suitable learning materials to the learners' requirements?*

According to the preliminary studies, the learning materials stored in a single content granularity cause the inefficient problem in providing content having adaptive presentation to a new learner. Thus, a Multi-Granularity Content model (MGC) is proposed to represent and store the learning materials as multiple granularities. For a new requirement, the coarse-grained learning material fulfilling the most learning needs is retrieved as the main body of the provided content. Afterward, the fine-grained parts of the retrieved material, which are less appropriate for the learner, are replaced by other fine-grained parts to enhance the quality of the adapted content. The content adaptation mechanism adapts learning materials from coarse-grained to fine-grained can prevent the combination explosion problems and the combination costs of detailed chunks.

3.3 Process Skill Diagnosis Subproblem

Learners need to monitor and reflect on their learning status in the monitoring and reflecting phases of self-regulation, so learning diagnosis mechanisms were proposed to support learners to evaluate their own learning. In the linear learning process, all learners' learning portfolios are homogeneous, so assessing learners' learning performance and status is easy by ranking or scoring. However, in the non-linear learning process, all learners' learning processes are various, so how to assess the heterogeneous learning portfolio to provide the learning diagnosis is more difficult than the homogeneous ones. Teachers' high-level diagnosis knowledge can be generally applied for various learning processes, but the existing approaches only focus on evaluating learners' results of traditional tests. Without considering learners' detailed learning behaviors in learning activities, such as operations in a scientific inquiry experiment, the learning diagnosis cannot precisely capture learners' learning status and process skills, especially in the science education.

Thus, the **Process Skill Diagnosis Subproblem** is defined as *how to provde learning diagnosis for scientific learning, such that*

- *the heterogenerous learner portfolios generated in the scientific learning can be managed and organized,*
- *the teaching expertise can be applied to these diversified portfolios, and*
- *the diagnosis can find learners' weekness of concepts and process skills*?

To cope with the Process Skill Diagnosis Subproblem, a middle-level knowledge representation is needed to extract the learners' learning status from heterogeneous learning events and provide structural learner models for learning diagnosis. Thus, a Heterogeneous Knowledge Diagnosis model (HKD) is proposed where an Ability-Centered Level is defined to connect high-level diagnosis knowledge and low-level learning events. In the Ability-Centered Level, all the learning behaviors and test results are structured for further diagnosis. In the Ability-Centered Level, the background knowledge, including concepts or process skills, is represented as the ontology, where concepts and skills are represented as nodes and the prerequisite relations and extended relations are represented as the relations between nodes. All learning behaviors and test results are extracted and represented as predicates of learning status. For example, after learners get a score 0.8 of a concept c_1 in a test, a predicate is recorded as *Score*(c_1, 0.8), and after reading a lecture about c_1 during the inadequate reading time, the learning behavior is also be recorded as *LearningTime*(c_1, *inadequate*). Besides, assume a learner does a wrong operations about the measurement skill in the virtual lab, a predicate *WrongOperation*(*measurement*) is recorded. In order to extract the structured learning status from the heterogeneous learning events, the frame-based knowledge representation is used to model all the learning activities. For example, the frame of a reading activity records the lecture's expected reading time and its associated concepts. For an experiment-based test, the frame records all necessary and wrong operation patterns and their associated skills and concepts. The embedded rules are defined to transform a learner's learning events to the predicates in the Ability-Centered Level according to the slots of the frames. Besides, the high-level learning diagnosis knowledege can be represented by using rule-based representation, which can infer learning status and learning barriers from the predicate of learning status and the relations in the ontology of the Ability-Centered Level.

3.4 Interoperability of Scaffolding Providers in Adaptive Scaffolding Scheme

The three scaffolding providers can be interoperable to provide the complete adaptive scaffoldings for learners. As shown in Figure 3.3, in the planning phase of self-regulated learning, the Plan Scaffolding Provider based on Generalized Finite State Machines can provide the suggested learning activity $s_i \in S$ (Step 2) according to the learner's learner model $\mu_k \in \Sigma$ and the previous learning activity (Step 1).

PSP: $\Sigma \times S \rightarrow S$, *where* Σ is a set of learner models and S is a set of learning activities.

If the learner takes a reading activity, the Content Scaffolding Provider based on a Multi-Granularity Content Model can adapt the content $c_j \in C$ (Step 4) according to the requirements of learning activity s_i and the learner model μ_k (Step 3) to support the learner learning in the control phase.

CSP: $\Sigma \times S \rightarrow C$, *where* C denotes a set of contents.

The learner can read the content c_j or take a test in the suggested learning activity s_i and generate a set of learning events $e_l \in E$. The *Reading* represents the learner's behavior in the reading leanring activity and *Learning* represents the learning behavior in other learning activities:

Reading: S × C → E, where E denotes a set of learning events.

Learning: S → E

Finally, in the monitoring and the reflecting phases, the Suggestion Scaffolding Provider based on the Heterogeneous Knowledge Diagnosis Model can infer new learner model according to these learning events e_l (Step 5).

SSP: $E \times \Sigma \rightarrow \Sigma$

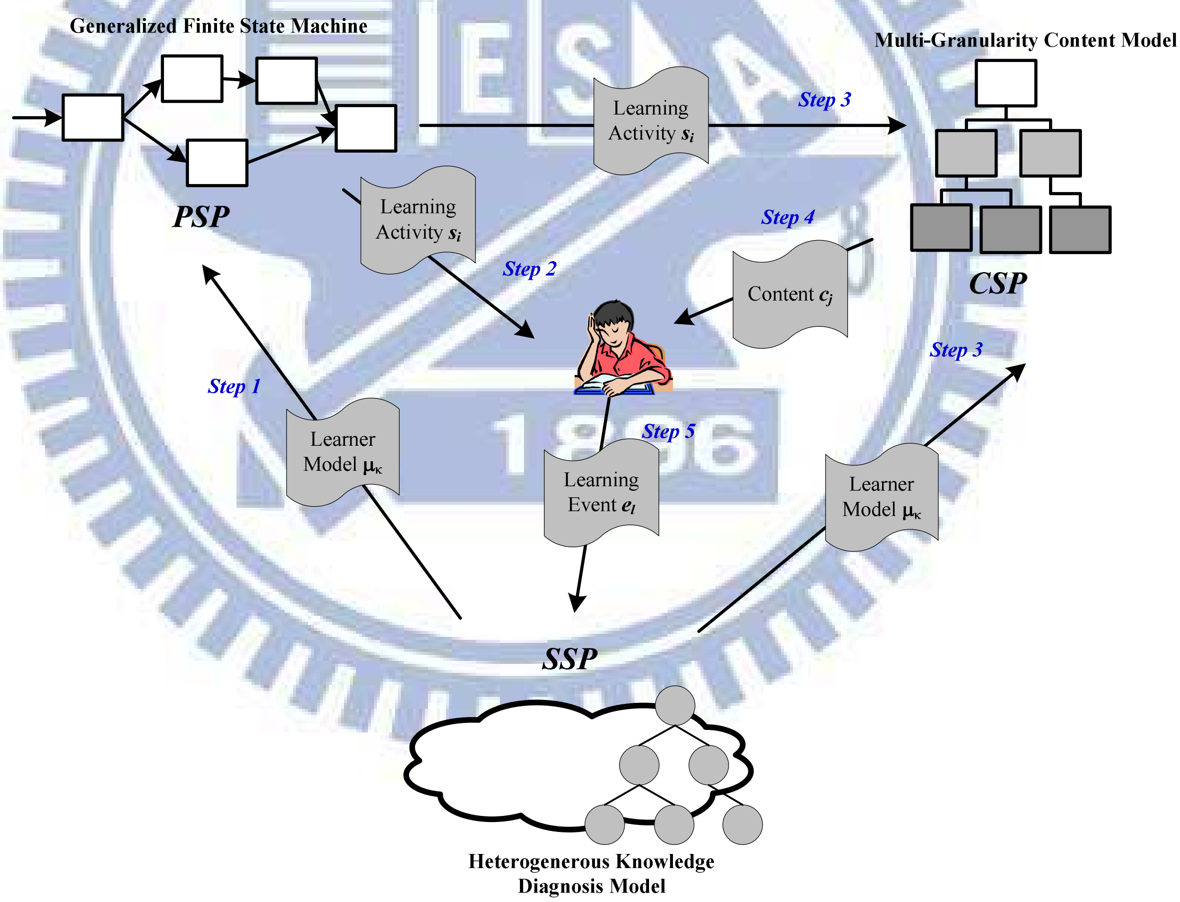


Figure 3.3: Knowledge interoperability between the three scaffolding providers

The three scaffolding providers in the scheme mentioned above can provide adaptive scaffoldings to help learners in their SRL processes. The information of learners' status can be shared among these scaffoldings providers to produce ongoing diagnosis and suggestions. In the following chapters, the three knowledge models used in the three scaffolding providers are introduced precisely.

Chapter 4 Generalized Finite State Machine

For the non-linear learning process reprentation, the existing learning process representation models either lack expressive power to express teaching strategies for complex learning portfolios or are non-intuitive to facilitate teachers to design. Thus, how to facilitate teachers to intuitively design the adaptive learning plan to guide learners in their planning phase is a critical issue. Thus, a generalized finite state machine is used to model the knowledge of learning plans. The finite state machine (S, Σ, s_0, δ, F) is an intuitive model, usually used to represent the process, where S denotes a set of states, Σ denotes a set of alphabets of possible inputs, s_0 denotes the initial state, δ denotes a transition function δ: $S \times \Sigma \rightarrow S$, and F denotes a set of final states. The generalized finite state machine (*GFSM*) is generalized from the traditional finite state machine, where the state S represents the leanring activities and transitions δ represent the recommended learning processes. Planning learning paths from the non-linear learning processes needs to refer to learners' concept abilities, styles, and previous learning paths. However, in the traditional finite state machine, the inputs Σ, which are a set of alphabets, are difficult to represent the complex learner portfolio, because the single-alphabet input needs to describe multiple attributes of a learner's portfolio, such as concept abilities, and learning styles. Thus, in the *GFSM*, a compound input is used to represent multiple attributes of a learner’s portfolio. Because of the compound inputs, the traditional transition function, which is a mapping table between states, input alphabets, and the next states, is needed to be generalized to implement the *GFSM*. The rules of the disjunction normal form (DNF) are used in the new transition function to express the teachers’ learning-path-selecting strategies.

4.1 Definition of Generalized Finite State Machine

The definitions of *GFSM* are as follows:

$GFSM = (S, \Sigma, s_0, \delta, F)$: a generalized finite state machine.

$S = \{s_0, s_1, \ldots, s_n\}$: a set of states, which represent learning activities.

$\Sigma = \{\mu_1, \mu_2, \ldots, \mu_m\}$: a set of compound inputs μ_i, which represent learner models.

$\mu_i = \{a_{i1}, a_{i2}, \ldots, a_{iN}\}$: a set of attributes a_{ij}. Assumed there are N attributes recorded in the learner model in the scheme.

s_0: initial state.

δ: $S \times \Sigma \rightarrow S$: a transition function where DNF rules are embedded.

$F \subset S$: a set of final states

4.2 Rule Class Generation

In order to implement the GFSM, which adopts DNF rules to represent learning-path-selecting strategies, the rule-based approach is used to conduct the execution of GFSM. Besides, in order to facilitate rule management, the New Object oriented Rule Model (NORM) architecture [63, 87, 88, 96] is used. NORM is a knowledge model of rule base, where the rules about the same knowledge domain are collected into a rule class (*RC*). Each rule class can include or refer to some other rule classes, and these relevant rule classes will form a set of rule objects (*RO*), which can be dynamically linked and perform cooperative inference. Accordingly, a *GFSM* can be considered as a knowledge object and the transition function can be represented as rules, which can be conducted by an existing inference mechanism. The algorithm of Rule Class Generation is proposed to transform a GFSM to an RC, as shown in Algorithm 4.1, where the state facts f_{now} and f_{next} are used as the variables to store the names of the current state and the next state generated by the inference. The learning status facts $\{f_{a1}, f_{a2}, \ldots, f_{aN}\}$ are generated to store the values of the compound inputs μ. Thus, the rule r can refer to the current state f_{now} and the learning status $\{f_{a1}, f_{a2}, \ldots, f_{aN}\}$ to determine the name of the next state f_{next}.

Algorithm 4.1: Rule Class Generation

Input: *GFSM*

Output: *RC*

Step 1: Create a rule clase *RC*.

Step 2: Generate a fact f_{now} to record the name of the last state and add f_{now} into *RC*.

Step 3: Generate a fact f_{next} to store the name of the next state and add f_{next} into *RC*.

Step 4: Generate facts $\{f_{a1}, f_{a2}, ..., f_{aN}\}$ to record all the attributes of the learning status and add them into *RC*.

Step 5: Generate a rule r for each transition mapping tuple $\delta(s_i) = s_j$ and its embedded DNF rule R as

"If (f_{now} = 's_i') $\wedge$ R => f_{next} = 's_j' " and add r into *RC*.

Step 6: Return *RC*.

Example 4.1:

Assumed the *GFSM* = (S, Σ, s_0, δ, F) where S = $\{s_0, s_1, s_2\}$ denotes the three learning activities and s_0 is the initial activity. $F = \{s_1, s_2\}$ denotes that the learning activities s_1 and s_2 are both final activities. Each input μ in Σ contains the values of four attributes $\{c_1, c_2, style\}$, where c_1 and c_2 denote the abilities of two concepts and *style* denotes the learning style. The transition function δ contains two rules: $\delta(s_0, \mu) = s_1$ if μ satisfy the embedded rule R_1: $c_1 > 0.5 \wedge c2 > 0.5 \wedge style = visual$; and $\delta(s_0, \mu) = s_2$ if μ satisfy the embedded rule R_2: $c_1 \leq 0.5 \vee c2 \leq 0.5$. The two transition rules mean that if the learner's scores of concept c_1 and c_2 are both greater than 0.5 and the learning style is visual, the suggestion of the next activity is s_1, or the the suggestion of the next activity is s_2, otherwise. Thus, by using the Rule Class Generation algorithm, the rule class of *GFSM* can be generated as two state facts, f_{now} and f_{next}, and three learning status facts, f_{c1}, f_{c2}, and f_{style}. The two rules can be generated corresponding to the two rules in the transition function δ. The rule r_1 generated according to R_1 is "*If* (f_{now} = 's_0') $\wedge$ ($f_{c1} > 0.5 \wedge f_{c2} > 0.5 \wedge f_{style} = visual$) => f_{next} = 's_1'" and r_2 generated according to R_2 is "*If* (f_{now} = 's_0') $\wedge$ ($f_{c1} \leq 0.5 \vee f_{c2} \leq 0.5$) => f_{next} = 's_2'".

4.3 Extended Model for Non-Linear Learning Process

The *GFSM* can clearly represent the non-linear learning process and the learning-path-selecting strategies. Teachers can design their teaching strategies by using GFSM and it can suggest the next learning activities to learners when they cannot by plan their learning by themselves. The process of applying *GFSM* to help planning includes the designing and executing phases as shown in Figure 4.1. In the designing phase, a non-linear learning plan can be designed via a graphical authoring tool to help teachers easily design learning-path-selecting strategies with various learning resources and activities, and the Rule Class Generation, using Rule Class Generating Algorithm is used to generate the rule class of learning sequencing controls from the DNF rules embedded in the *GFSM*. In the executing phase, the rule class is used in an Adaptive Learning Planning to suggest adaptive learning plan to learners. Three kinds of learning resource repository are provided: learning content repository can retrieve and display SCORM compliant learning contents, test item repository can provide test items and perform examination, and learning application repository contains the registration of learning services, which are provide by other learning systems, such as virtual laboratories and simulation-based tests, and can be executed and communicated via web services. Accordingly, the states of *GFSM* are also defined as three types: $s_i \in \boldsymbol{N_{LA}} \cup \boldsymbol{N_{AP}} \cup \boldsymbol{N_{EA}}$, where N_{LA} is a set of states denoting lecturing activities, such as an online-content-reading activity, N_{AP} is a set of states denoting education applications, such as virtual lab assessment, and N_{EA} is a set of states denoting examination activities, such as an online test.

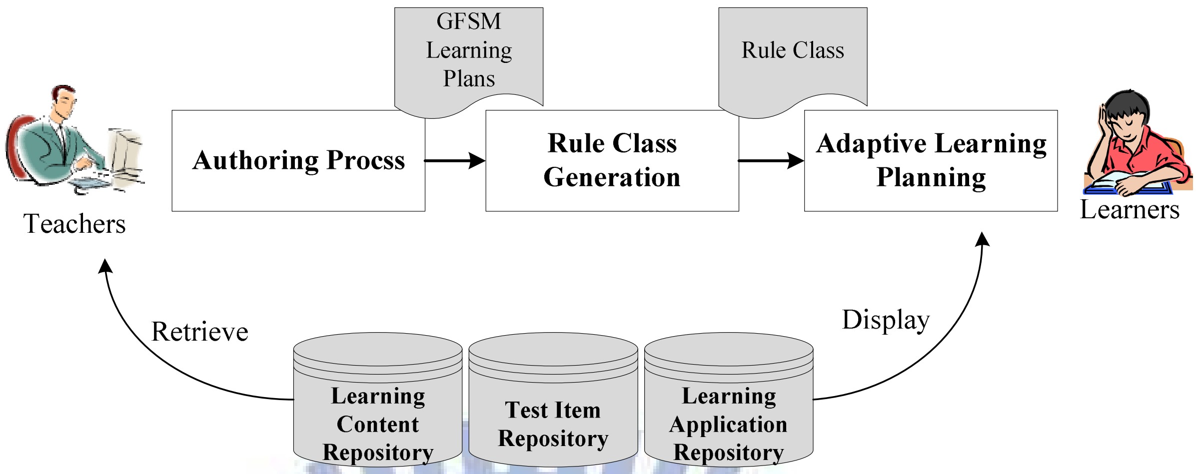


Figure 4.1: Designing and Executing Phase of Object Oriented Leanring Activity System

4.3.1 Adaptive Learning Planning

Figure 4.2 illustrates the flowchart of the Adaptive Learning Planning. In the beginning of the process, the rule class and GFSM are loaded into the rule base, and the learning activity of the initial state is fired. The corresponding learning resources are suggested to learners using a proper display interface according to the type of the learning resources. After the learner finishes the current learning activity, the inference process is triggered with the latest state and the learning status to find the next state until the final state is reached.

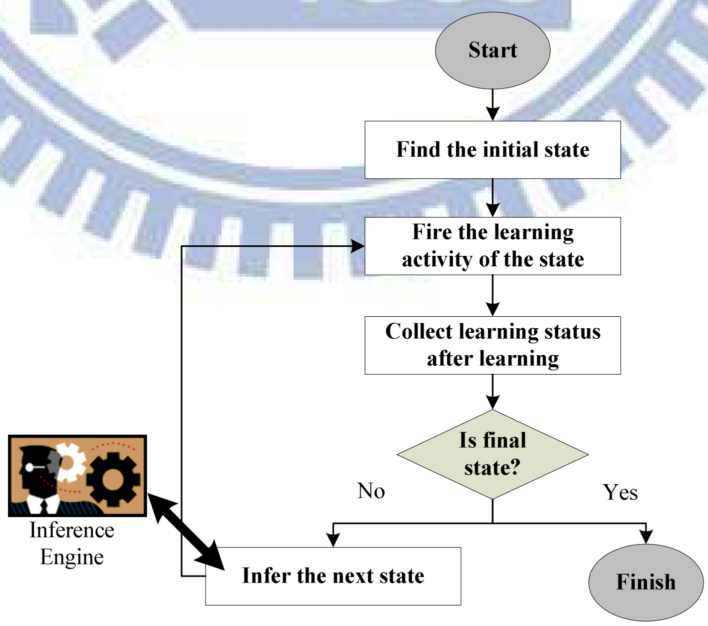


Figure 4.2: Flowchart of Rule based adaptive learning method

The Algorithm of Adaptive Learning Planning is shown as follows, where the fact f_{now} stores the name of the current state, such as 's_0' or 's_1'. The current activity is displayed according to the category of the current state. After finishing the current activity, the name of the next state can be infered by using the inputted rule class with f_{now} and $\{f_{a1}, f_{a2}, ..., f_{aN}\}$, which stored all values of learning status, such as abilities of concepts and learning style.

Algorithm 4.2: Adaptive Learning Planning
Input: The *GFSM* and the corresponding rule class
Step 1: Initially, f_{now} = 's_0'
Step 2: **Do loop**
  2.1: Find s_i in *GFSM* where f_{now} = 's_i'
  2.2: If $s_i \in N_{LA}$ **Then** show learning items in a SCORM compliant content displayer
    Else if $s_i \in N_{AP}$ **Then** show learning items in a learning application displayer
    Else if $s_i \in N_{EA}$ **Then** show learning items in a test item displayer
  2.3: **If** $s_i \notin F$, **Then** the learning activity is finished.
    Else Trigger the inference process with inputted rule class:
      Set μ_j, represented the current learners' status, into $\{f_{a1}, f_{a2}, ..., f_{aN}\}$.
      Trigger inference to get new value of f_{next}.
      Assign the value of f_{next} into f_{now}.
  End loop

4.4 Experiment and Experimental Result

The concept of *GFSM* is applied to implement a learning system, named Object-Oriented Learning Activity System (OOLA) [60]. The in-service teachers were invited to design a scientific learning activity, named "*The evaporation, condensation and boil of water*" in the OOLA system. The course structure and the teaching strategies are described in Appendix 1. To evaluate the effectiveness of OOLA system, we apply the one-group pretest-posttest design for the 62 learners of 5th graders in an elementary school in Taiwan. Firstly, let the pretest examination score of concepts of "*The evaporation, condensation and boil of water*" be the covariate variable. After one month learning with OOLA system, the posttest examination score of the same scope is chosen as the dependent variable. Referring to the pretest result, the learners are partitioned into high grade group and low grade group. The pairwise t-test and discussion of all learners, high grade group and low grade group are as follows.

The pairwise t-test of all learners

Table 4.1: The pretest-posttest of learning achievement

Learner Group		Mean	Size	Standard Deviation	Mean difference
Learning Achievement	pretest	25.7419	62	3.1516	.4002
	Posttest	28.1290	62	4.1429	.5261

Table 4.2: The one-group pretest-posttest t-test

Pairwise t-test	Variance of Paired Difference			t
	Mean	Standard Deviation	Standard Error of Mean	
pretest-posttest	2.3871	3.9187	.4977	4.797*

*$p < .001$

Table 4.1 and *Table 4.2* show that there is significant difference between the pretest and the posttest mean scores (t = 4.797, $p < .001$). It is deduced that the Scaffolding Instruction designed by OOLA system is effective for learners.

The pairwise t-test of high grade group

Furthermore, referring to the pretest result, the learners are partitioned into high grade group and low grade group. The pairwise t-test in each group is also investigated to analyze the pretest-posttest of learning achievement.

Table 4.3: The pretest-posttest of learning achievement of high grade group

Learner Group		Mean	Size	Standard Deviation	Mean difference
Learning	Pretest	28.3548	31	1.5822	.2842
Achievement	Posttest	29.1290	31	3.5846	.6438

Table 4.4: The one-group pretest-posttest t-test of high grade group

Pairwise t-test	Variance of Paired Difference			*t*
	Mean	Standard Deviation	Standard Error of Mean	
pretest-posttest	.7742	3.5657	.6404	1.209

*$p < .001$

In *Table 4.3* and Table 4.4, the means scores of the pretest and the posttest have no significant difference ($t = 1.209$, $p > .001$). It is deduced that the Scaffolding Instruction is not effective for high grade learners.

The pairwise t-test of low grade group

Table 4.5: The pretest-posttest of learning achievement of low grade group

Learner Group		Mean	Size	Standard Deviation	Mean difference
Learning	pretest	23.1290	31	1.8928	.3400
Achievement	posttest	27.6452	31	3.3221	.5967

Table 4.6: The one-group pretest-posttest t-test of low grade group

Pairwise t-test	Variance of Paired Difference			*t*
	Mean	Standard Deviation	Standard Error of Mean	
pretest-posttest	4.5161	3.6503	.6556	6.888*

*$p < .001$

In *Table 4.5* and *Table 4.6*, the mean scores of the pretest and the posttest have significant difference ($t = 6.888$, $p < .001$). It is deduced that the Scaffolding provided by OOLA system is effective for low-grade learners. After further discussion with learners, we found that the high-grade learners tend to learning by interaction with other learners or teachers. Therefore, the individual learning in HLE without discussion with peers and teachers is difficult to improve their learning performance. On the contrary, the low-grade learners tend to find the solutions from learning objects. It results in that the scaffoldings of OOLA system can assist them in finding the learning objects based on their misconception. Therefore, the scaffoldings of OOLA system is effective especially for low-grade learners.

Chapter 5 Multi-Granularity Content Model

For learners having various portfolios, prior knowledge, and learning devices, a learning content can be transformed to various versions to fulfill the diverse requirements. As mentioned in Chapters 2 and 3, adapting the single-granularity learning content to diverse requirements is inefficient. If the content versions are managed as coarse-grained versions, the huge amont of versions need to be managed for diverse requirements. If the fine-grained content versions are used, combining fine-grained versions to generate new content for diverse requests could cause the combination explosion. Thus, a Multi-Granularity Content Model is proposed to represent and store the learning contents as multiple granularities, including page, block, and media, where a learning content can be retrieve as a coarse-grained content or a set of fine-grained contents.

For a new request, the most suitable coarse-grained version is retrieved as the main body of the output. If the response time is acceptable, the fine-grained parts of the retrieved content, which are less appropriate for the learner, are replaced by other fine-grained parts to enhance the quality of the adapted content. The content adaptation mechanism adapts learning materials from coarse-grained to fine-grained can prevent the huge number of prepared contents and the problem of combination explosion of detailed chunks.

5.1 Definition of Multi-Granularity Content Model

The definitions of the Multi-Granularity Content Model are as follows:

- $MGC = (F, N, SF)$: Multi-Granularity Content Model.
  - F: a set of possible feature sets.
  - $N = \{n_0, n_1, \ldots, n_m\}$: a set of nodes of all granularities in cases.
    - $n_i = (F_i, child_i, level_i, content_i)$: a node of a content version.
    - $F_i \in F$: a set of features

- $child_i \subset N$ is a set of children nodes. If n_i is a leaf, $child_i = \{\}$.
- $level_i$: the level of granularity, where $n_i \in child_j$ *iff* $level_j = level_i - 1$.
- $content_i$ denotes the original content of the version n_i. $content_i = content_j$ iff n_i and n_j are adapted from the same content.

■ SF: $F \times \Sigma \rightarrow \Re$: a satisfaction function, where $\Re$ is the degree of the adaptation quality and Σ is a set of inputted learner models.

The *MGC* can be applied to the learning content domain to define the detailed definitions as follows:

- If $level_i = 0$, n_i denotes a page version of a learning content; if $level_i = 1$, n_i denotes a block version of a page; and if $level_i = 2$, n_i denotes a media version of a block.
- $\mathrm{F_i = CP_i \mid level_i = 0}$
  - $CP_i = \{c_1, c_2, ...\}$ is a set of concept properties, denoting the concepts taught in the page n_i.
- $F_i = HP_i \cup LP_i \cup \{b_i\} \mid level_i = 1$
  - $HP_i = \langle a_1, a_2, \ldots, a_n \rangle$: every attribute ($a_j$) denotes a set of features about hardware properties, such as the machine type (PDA or smartphone), Central Processing Unit (CPU) speed, memory capacity, screen size, and sound rate.
  - $LP_i = \langle b_1, b_2, \ldots, b_k \rangle$: every attribute ($b_j$) denotes a set of features about the learner properties, e.g., maximum delivery time, preferred picture format ordering, preferred audio property, media switch, preferred content type, cognitive style, learning style, etc. Thus, we can initially define the LP=<*Delivery Time* (DT), *Preferred Picture Format Ordering* (PPFO), *Picture Switch* (PS), *Audio Switch* (AS)>.
  - b_i denotes the suitable network bandwidth to this version.
- $\mathrm{F_i = MP_i \cup \{type_i, size_i\} \mid level_i = 2}$

- MP_i denotes the media parameters of the media-level nodes, where the features depend on $type_i$. If type_i = *image*, $MP_i = \{width_i, hight_i, color_i, mType_i\}$; if type_i = *audio*, $MP_i = \{precision_i, rate_i\}$; and if type_i = *video*, $MP_i = \{width_i, hight_i, precision_i, rate_i\}$.
- $color_i$ denotes the color depth, $mType_i$ denotes the image type, $precision_i$ denotes the sound precision, and $rate_i$ denotes the sound rate.
- $size_i$ denotes the size of this media version.

- $\sum = CP_i \cup HP_i \cup LP_i \cup \{b_i\}$: a learner's request.

Example 5.1:

A n_0 with $level_i = 0$ denotes a page-level node, where the features $F_0 = \{c_1, c_2\}$ contains two concepts teached in the $content_0$. c_1 is "*Freezing Point*" and c_2 is "*Temperature Drop*".

From n_1 to n_{15} are the block versions of n_0, where $level_i = 1$. The nodes contains a set of features $HP_i \cup LP_i \cup \{b_i\}$, where HP_i = <1, 400, 128, 480, 640, 16, 16, 44> denotes that a learner uses a PDA (1) with 400 Mhz, 128 MB, 480×640 resolution, 16 bits color depth, 16 bits sound precision and 44 KHz sound rate (U denotes Unsupported) under 80 kbps bandwidth (b_i) to retrieve the content, and LP_i = <5, JPGB, 1, 0> denotes that the maximum delivery time (DT) is less equal than 5 seconds (sec.), the order of Preferred Picture Format Ordering (PPFO) is JPG (J) > PNG (P) > GIF (G) > BMP (B), the switch attribute of media, PS=1, enables to show the picture, and the AS=0 disables the audio play, respectively. Table 5.1 shows the example with 15 nodes having $level_i = 1$. The attribute definitions of *LP* and *HP* can be extended to meet the various requirements.

Table 5.1: Example of block-level nodes having $level_i = 1$

	Bandwidth (b)	Hardware Properties (HP)	Learner Properties (LP)
n_1	213	<2, 528, 384, 320, 480, 16, 32, 120>	<7, JBGP, 1, 1>
n_2	175	<2, 600, 384, 320, 480, 24, 16, 40>	<2, GPBJ, 0, 1>
n_3	487	<0, 1200, 4000, 1366, 768, 32, 16, 300>	<2, JGPB, 1, 0>
n_4	223	<2, 528, 288, 320, 480, 16, 8, 30>	<3, JBPG, 1, 0>
n_5	281	<2, 528, 384, 320, 480, 16, 32, 120>	<7, PJGB, 0, 1>
n_6	69	<0, 2000, 8000, 1366, 768, 32, 32, 500>	<1, GPBJ, 1, 0>
n_7	232	<2, 528, 288, 320, 480, 16, 8, 30>	<5, JPGB, 0, 1>
n_8	290	<1, 1000, 448, 480, 800, 24, 16, 140>	<1, GPJB, 1, 0>
n_9	95	<0, 1200, 4000, 1366, 768, 32, 16, 300>	<1, BJGP, 0, 0>
n_{10}	167	<0, 1200, 4000, 1366, 768, 32, 16, 300>	<5, GPJB, 1, 0>
n_{11}	220	<0, 1200, 4000, 1366, 768, 32, 16, 300>	<5, JPGB, 0, 1>
n_{12}	326	<2, 528, 288, 320, 480, 16, 8, 30>	<4, JPGB, 0, 0>
n_{13}	339	<2, 528, 288, 320, 480, 32, 8, 20>	<7, PBGJ, 0, 0>
n_{14}	313	<2, 528, 288, 320, 480, 32, 8, 20>	<4, GJPB, 1, 1>
n_{15}	95	<2, 528, 384, 320, 480, 16, 32, 120>	<4, PBJG, 0, 0>

5.2 Content Version Management Scheme

Content versions of each granularity are stored in MGC Base and managed by Content Version Management Sheme for serving learners' requests, as shown in Figure 5.1. The page-level nodes in the MGC are managed in the Page Version Base. The block-level nodes record all versions of blocks adapted in the previous adaptation processes, so an efficient retrieval mechanism is necessary for the large amount of nodes. These block-level nodes are processed by a Case Decision Tree Construction process to generate decision tree stored in a Block Version Base according to the hardware and learner properties to facilitate to efficiently retrieve appropriate nodes. All versions of media in blocks are managed in the Media Version Base. When retrieving a new case, the learner's request is firstly used to retrieve an appropriate pages according to concept properties (*CP*) in the request and page-level nodes. If the original blocks in the pages cannot satisfy the request, an Adaptation Decision Process is executed to retrieve the appropriate block-level nodes generated in the previous adaptation. If these previous block-level nodes cannot still satisfy the request, a new media object can be trandcoded in the Learning Content Synthesis.

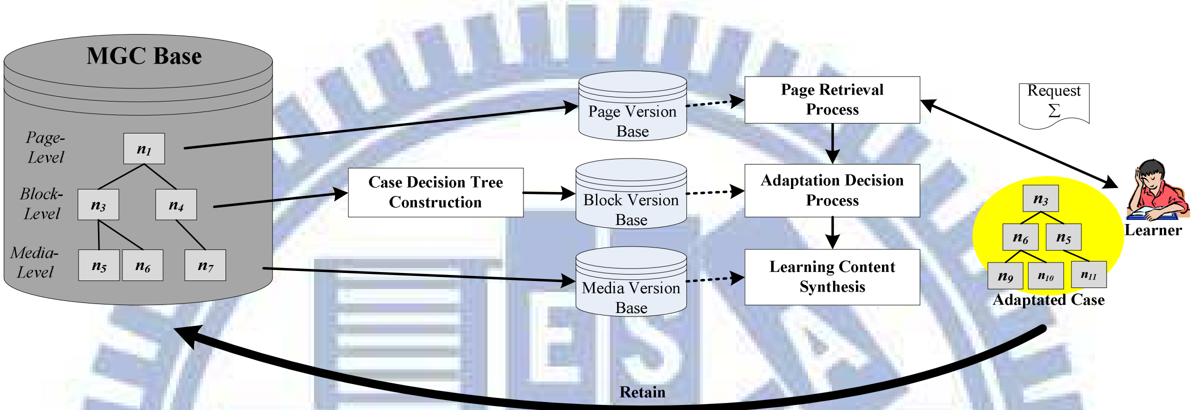


Figure 5.1: Content Version Management Sheme

In this section, we will describe how to use existing block-level nodes to construct a Content Adaptation Decision Tree (CADT) in the Content Version Management Scheme. The CDT can be used to efficiently and quickly determine the suitable adapted block-level nodes for learners according to the mobile device features, the preferences of learners, and network bandwidth. As shown in Figure 5.2, the Case Decision Tree Construction process includes Content Version Clustering, based on ISODATA Clustering algorithm, and Content Version Cluster Decision Tree Construction, based on ID3 algorithm.

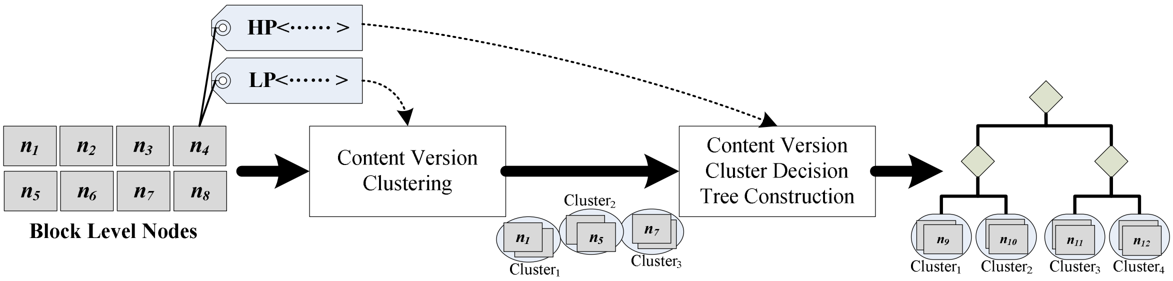


Figure 5.2: Case Decision Tree Construction

To apply the ISODATA clustering approach, a similarity measure estimating the similarity value between two block-level nodes based on the *LP* must be determined. Because the attribute of an *LP* might consist of a **numerical attribute**, e.g., *maximum delivery time*, and a **symbolic attribute**, e.g., *preferred picture format ordering*, the similarity measure of an *LP* can be formulized by means of the distance measure approach as follows:

Given two LP_i=<a_1, a_2,…, a_n> and LP_j=<b_1, b_2,…, b_n>, the similarity measure of numerical attribute can be formulized as follows:

$SimofNum_k = 1 - \frac{|a_k - b_k|}{Max_k - Min_k}$, where $1 \leqq k \leqq n$, the Max_k and the Min_k are the predefined maximum and minimum values of *k-th* attribute in an *LP*, respectively.

Regarding the symbolic attribute in an LP, the value, *JPGB*, is like a *string*. To calculate the similarity between two symbolic attributes, their string-based values can be encoded into a numerical value by the numerical order of predefined symbol priority. For instance, the numerical value of string *JPGB* can be encoded as '1234' based on the priority order definition {"J"=1, "P"=2, "G"=3, "B"=4}. Also, the maximum value will be the '4321' of the string *BGPJ*. The symbolic attribute can thus be transformed into a numerical value and its similarity can be measured by the $SimofNum_k$ formula. Because attributes in an LP may have different degrees of importance, we define a *Weight Vector* (*WV*), which can be manually defined by a learner, to adjust for the degree importance of each attribute. Therefore, the similarity measure between two LPs can be formulated as:

$Similarity_{LP}(LP_i, LP_j) = \sum SimifNum_k(a_k, b_k) \times w_k$, where $w_k \in WV$, $\sum w_k = 1$, and $l \leq k \leq n$.

To evaluate when to split and merge the cluster, the $Deviation_{LP}$, which is used to calculate the standard deviation of the samples, must be defined as:

$Deviation_k^{LP} = \left|\frac{a_k - b_k}{Max_k - Min_k}\right|$, where $1 \leqq k \leqq n$, the Max_k and the Min_k are the predefined maximum and minimum values of k_{th} attribute in an LP, respectively.

Example 5.2:

Given two LPs, LP_1 = <3, JPGB, 1, 0> and LP_2 = <2, JGBP, 1, 1>, and a learner predefined related attribute WV = <0.5, 0.3, 0.1, 0.1>. We can apply the above similarity measure to calculate the similarity between LP_1 and LP_2. For example, the similarity of the numerical attribute, *Delivery Time* (DT), between LP_1 and LP_2 is:

$$SimofNum_1 = 1 - \frac{|a_1 - b_1|}{Max - Min} = 1 - \frac{|3-2|}{5-1} = 0.75$$

The similarity of the symbolic attribute, Preferred Picture Format Ordering (PPFO), is:

$$SimofNum_2 = 1 - \frac{|1234 - 1423|}{4321 - 1234} = 1 - \frac{189}{3087} = 0.938$$

Hence, by the same way, the similarity between LP_1 and LP_2 is:

$$
\begin{aligned}
&Similarity_{LP}(LP_1, LP_2) \\
&= 0.75 \times 0.5 + 0.938 \times 0.3 + (1 - (\frac{|1-1|}{1-0})) \times 0.1 + (1 - (\frac{|0-1|}{1-0})) \times 0.1 \\
&= 0.7564
\end{aligned}
$$

$$Deviation_1^{LP} = |\frac{3-2}{5-1}| = 0.25$$

5.2.1 Content Version Clustering

An Content Version Clustering based on ISODATA is proposed to group these *LP*s into several clusters according to the aforementioned similarity and deviation measure, shown in Content Version Clustering Algorithm (*CVClustering*). After applying the algorithm, the block-level nodes in Table 5.1 can be grouped into three clusters, as depicted in Table 5.2. The clustering result shows that the versions in Cluster 1 can satisfy a learner who prefers pictures and does not want audio. The versions in Cluster 3 can provide both pictures and audio, and the other versions are clustered into Cluster 2.

Algorithm 5.1: Content Version Clustering Algorithm (*CVClustering*)

Symbols Definition:

***DT*: the Delivery Time (DT) in a learner propoerties vectors (*LP*).

LP_{set}: the set of *LP*.

***K*: the initial number of clusters.

***C*: a cluster with several learner preference vectors (*LP*).

***CC*: the Center of Cluster.

C_{set}: the set of clusters with the Center of Cluster (*CC*)

T_s: the split threshold (Standard Deviation) for splitting a cluster into two ones.

T_m: the merge threshold (Mean Distance) for merging two clusters into one.

T_n: the minimum number of the members in a Cluster for deleting a cluster.

T_i: the maximum iteration number for executing the clustering process

T_p: the minimum number of Cluster pair for merging clusters process.

Input: LP_{set}, K, T_s, T_m, T_n.

Output: The set of Clusters, C_{set}.

Step 1: Initial Clusters Selection:

1.1: *For i* = 1 to *K*.

Randomly select $LP_i \in LP_{set}$ to insert LP_i into C_i with $CC_i=LP_i$ and then insert C_i into C_{set}.

Step 2: ISODATA Clustering Process:

2.1: Execute the following sub-Steps (2.2-2.6) repeatedly until there is no difference between two iterations or the amount of iteration exceeds T_i.

2.2: Insert each $LP_j \in LP_{set}$ into appropriate cluster $C_i \in C_{set}$ according to the $Similarity_{LP}(CC_i, LP_j)$.

2.3: Delete the C_i if the number of *LP* is less than T_n.

2.4: Split a C_i into two clusters according to T_s and T_n.

2.5: Merge two clusters into one according to T_m and T_p.

2.6: Re-compute the Cluster Center (CC_i) for each $C_i \in C_{set}$.

Step 3: Output the C_{set}.

Table 5.2: Result of applying CVClustering with the cluster parameters (K =5, T_s =0.01, T_m =1.0, T_n =1, T_i=50, T_p=1) based on data in Table 5.1

Cluster Label	Block-level Nodes
1	{n_3, n_4, n_6, n_8, n_{10}}
2	{n_2, n_5, n_7, n_9, n_{11}, n_{12}, n_{13}, n_{15}}
3	{n_1, n_{14}}

5.2.2 Content Version Cluster Decision Tree Construction

After the clustering process, each cluster will be tagged with a label, as shown in Table 5.2. Determining a suitable cluster for a new request is an issue which can be resolved by using the decision tree approach. Based on the Hardware Properties (*HP*s) in these block-level nodes, with cluster labels defined in Table 5.2, we can apply a decision tree induction algorithm, Iterative Dichotomiser 3 (ID3) [74], to create a Content Adaptation Decision Tree (CADT). ID3 can process only the symbolic value of an attribute, so the numerical attribute values of the HP in Table 5.1, e.g., CPU speed, system memory, etc., have to be discretized by the following approach.

In all HPs, ℓ and μ are the minimal and maximal values of an attribute, respectively. Let $\Delta=(\ell-\mu)/N$, where N is the number of desired discrete ranges. Then, a numeric value of an attribute can be mapped into the symbolic value. For example, given N = 3, the corresponding symbolic values are **L** in [ℓ, $\ell+\Delta$], **M** in [$\ell+\Delta$, $\ell+2\Delta$], and **H** in [$\ell+2\Delta$, $\ell+3\Delta$]

Therefore, the numerical attribute of *HP* in Table 5.1 can be mapped into several discrete ranges, as shown in Table 5.3.

Table 5.3: Result of mapping the numerical value in HP

Numerical Attribute	**Representative Symbol**
CPU Speed (CPU)	L: *Low*, M: *Medium*, H: *High*
System Memory (SM)	L: *Low*, LM: *Low-Medium,* MH: *Medium-High*, H: *High,*
Screen Horizontal Size (SHS)	T: *Tiny*, S: *Small,* M: *Medium,* L: *Large*
Screen Vertical Size (SVS)	T: *Tiny*, S: *Small,* M: *Medium,* L: *Large*

Example 5.3:

Table 5.4 shows six *HP* data with cluster label, which have been classified into two subsets: {4, 7, 12} and {5, 15, 1} according to the attribute, "*Sound Precision.*" The expected information needed to classify six samples is given by the information gain (*I*):

I (the number of nodes in C_1, the number of nodes in C_2, the number of nodes in C_3)

$$
\begin{aligned}
&= I(1,4,1) \\
&= -\left(\frac{1}{1+4+1}\right)\log_2\left(\frac{1}{1+4+1}\right)-\left(\frac{4}{1+4+1}\right)\log_2\left(\frac{4}{1+4+1}\right)-\left(\frac{1}{1+4+1}\right)\log_2\left(\frac{1}{1+4+1}\right) \\
&= 1.252
\end{aligned}
$$

The Entropy (E), or expected information based on the partitioning into two subsets by the attribute, "Sound Precision," is given by:

E(Sound Precision)

$$
\begin{aligned}
&= \frac{(1+2)}{(1+4+1)}I(1,2)+\frac{(2+1)}{(1+4+1)}I(2,1) \\
&= \frac{3}{6}(-\frac{1}{3}\log_2\frac{1}{3}-\frac{2}{3}\log_2\frac{2}{3})+\frac{3}{6}(-\frac{2}{3}\log_2\frac{2}{3}-\frac{1}{3}\log_2\frac{1}{3}) \\
&= 0.918
\end{aligned}
$$

Finally, the encoding information that would be gained by branching on attribute "*Sound Precision*" is

Gain(*Sound Precision*) = ***I***(1, 4, 1) - ***E***(*Sound Precision*) =1.252 - 0.918 = 0.334.

Table 5.4: HP in block-level nodes with cluster label classified by attribute, "Sound Precision"

Nodes	**HP in the Node**	**Cluster Label**
n_4	<2, 528, 288, 320, 480, 16, <u>8</u>, 30>	1
n_7	<2, 528, 288, 320, 480, 16, <u>8</u>, 30>	2
n_{12}	<2, 528, 288, 320, 480, 16, <u>8</u>, 30>	2
n_5	<2, 528, 384, 320, 480, 16, <u>32</u>, 120>	2
n_{15}	<2, 528, 384, 320, 480, 16, <u>32</u>, 120>	2
n_1	<2, 528, 384, 320, 480, 16, <u>32</u>, 120>	3

Consequently, by means of the above ID3 approach, the information gain of each attribute (of each *HP*) in Table 5.4 will be computed. The attribute with the highest information gain will be chosen as the test attribute. A node is created and labeled with the attribute, branches are created for each value of the attribute, and the samples are partitioned accordingly. Table 5.1 depicts the result of applying the ID3 algorithm data.

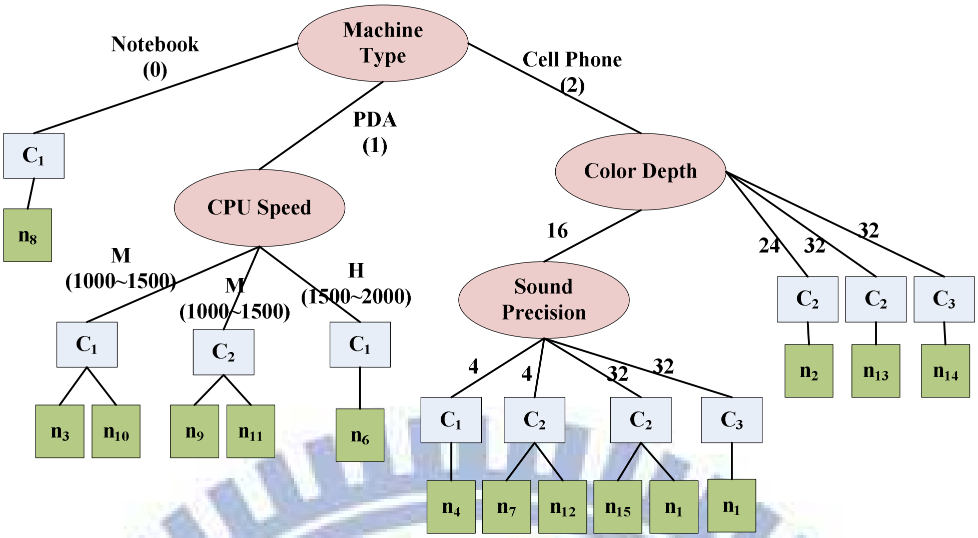


Figure 5.3: CADT based on HP in Table 5.1

5.2.3 Content Version Cluster Decision Tree Maintenance Process

As stated previously, after the clustering and decision tree construction processes are complete, all nodes n_i in the Node Pool, a temporary buffer, can be grouped into several clusters and retrieved by the CADT structure. In the CADT maintenance process (see Figure 5.4), all new nodes are first temporarily stored in a Node Pool. While the amount of nodes (N) in a Node Pool is more than a threshold, which is estimated automatically by the **CADT Rebuilding Equation** (Y=α+βX) generated by the ordinary least squares approach [37], the CADT is rebuilt automatically offline by the clustering and decision tree processes. Then, these processed nodes in the Node Pool will be shifted to the final storage and become the historical nodes indicated by the newly rebuilt CADT structure. Each node indicates the associated media nodes consisting of original or adapted versions, all of which are stored in the Media Version Base. Moreover, in order to efficiently manage the storage space of the Media Version Base, the Utilization Rate (***UR***) is checked of every adapted media object version, except for its original version. If the ***UR*** of any adapted version n_i < Threshold, it will be deleted from the Media Version Base.

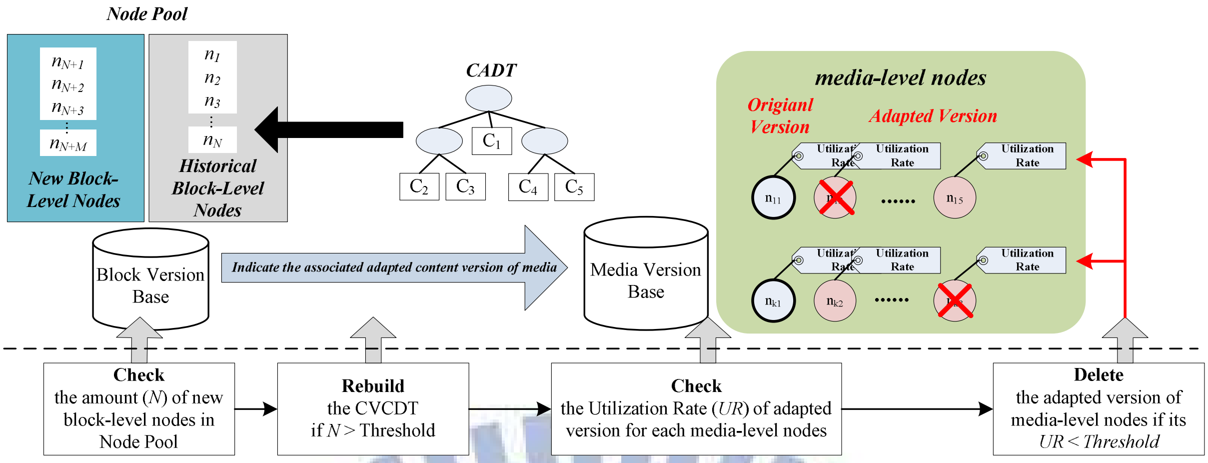


Figure 5.4: Flowchart of the CADT maintenance process

5.3 Content Adaptation Process

To meet diverse learner needs, including varied mobile device capabilities, network conditions, and individual learner preferences, the Content Adaptation Process (CAP) has been proposed to automatically determine an appropriate MP_{set} for all media-level nodes from the Media Parameter database, which records all possible media parameter value sets for media adaptation, to adapt and transcode all media resources in a desired page according to the requirement of the new Σ. The process is described below.

The first step of CAP is retrieving the most appropriate pages for the request Σ. The satisfaction degree of pages for the learner's request is measured by the intersaction of contained concept properties:

$$Satisfaction_{Page}(\Sigma, F_i) = \frac{CP_\Sigma \cap CP_i}{CP_\Sigma \cup CP_i}$$

The page-level node having the highest satisfaction degree is selected and the contained blocks are adapted if the blocks cannot fully satisfy the learner's requirements and the request time is acceptable.

5.3.1 Satisfaction Measure on the Quality of Media

In the CAP, we would like to determine an adapted media which can meet the requirement of a $\sum$ very well. Therefore, the satisfaction measure on the quality of media has been defined to estimate the satisfaction degree between the adapted media selected by CAP and the media requested by the learner.

Given $HP = <a_1, a_2, \ldots, a_m>$ and $MP_i = <b_1, b_2, \ldots, b_n>$, the similarity measure of each numerical attribute between HP and MP_i can be formulized as:

$$SimofNum(HP, MP_i) = Max\left(1 - \frac{|a_j - b_k|}{a_j}, 0\right)$$

where $1 \leqq j \leqq m$, $1 \leqq k \leqq n$.

Regarding the symbolic attribute of the image type between the MP_i and the requested $\sum$, e.g., *Preferred Picture Format Ordering (PPFO)*, the particular similarity measure of image type is formulized as:

$\boldsymbol{SimofImage_{Type}}(\text{PPFO} \in LP, mType_i \in MP_i) = 1 - (k - 1) \times 0.25$,

where k = the order of type in the string of PPFO.

We also define a ***Satisfaction Weight Vector*** (***SWV***) to adjust the degree of importance. The satisfaction measure on the quality of media between an $\sum$ and an MP in the media database can thus be formulated as:

$\text{Satisfaction}_{\text{QualityOfMedia}}(\sum, \text{MP}_i) =$

$\Sigma((\textbf{SimofNum}(\text{a}_\text{j} \in \text{HP}, \text{b}_\text{k} \in \text{MP}_\text{i}) \mid \textbf{SimofImage}_{\textbf{Type}}(\text{PPFO} \in \text{LP}, \text{mType}_\text{i} \in \text{MP}_\text{i})) \times \text{w}_\text{j})$,

where $w_j \in SWV$, $\Sigma w_j = 1$, and $1 \leqq j \leqq m$, $1 \leqq k \leqq n$.

Example 5.4:

Given a media-level node n_a whose f_a = { $width_i$, $hight_i$, $color_i$, $mType_i$, $type_i$, $size_i$ } = { 800, 400, 16, J, image, 160 } with SMV = <0.5, 0.1, 0.3, 0.1>, and a new $\Sigma = CP_i \cup HP_i \cup LP_i \cup \{b_i\} = \{c_1, c_2\} \cup$ {1, 1000, 448, **480**, **800**, **24**, 16, 140} ∪ {1, **GPJB**, 1, 0} ∪ {500}. Then, the satisfaction between Σ and n_a can be estimated as follows:

Satisfaction**$_{QualityOfMedia}$*(Σ, f_a) = 0.5 × ***SimofNum(480 ∈ *HP*, 800) + 0.1 × ***SimofNum***(800 ∈ *HP*, 400) + 0.3 × ***SimofNum***(24 ∈ *HP*, 16) + 0.1 × ***SimofImage**$_{Type}$*("GPJB" ∈ *LP*, 'J') = 0.5 × Max(0.33, 0) + 0.1 × Max(0.5, 0) + 0.3 × Max(0.66,0) + 0.1 × (1-(3-1) × 0.25) = 0.165 + 0.05 + 0.198 + 0.05 = 0.463.

5.3.2 Satisfaction Score of the Media Parameter

By means of the ***Satisfaction**$_{QualityOfMedia}$*(Σ, MP_i), we can understand which adapted media is more suitable to meet the requirements of a given Σ. However the response time to Σs will explicitly affect learner satisfaction. Accordingly, we take the response time into account and define the satisfaction score of the MP_i to estimate the satisfaction degree of applying the MP_i to adapt the original content $content_i$, whereby the most appropriate $MP_{set} = \{MP_1, MP_2, \ldots, MP_k\}$ can be determined by the CAP. The definition of the satisfaction score is as follows. The satisfaction score is determined by the $Satisfaction_{QualityOfMedia}$, but the score is multiplied by a penalty ratio if the response time exceeds the user-expected time.

$$SatisfactionScore_{MP}(Satisfaction_{QualityOfMedia}(\Sigma, MP_i), T_{expected}, T_{used})$$
$$= \begin{cases} \dfrac{satisfaction_{QualityOfMedia}}{1+(T_{used}-T_{\text{expected}})/T_{\text{expected}}}, & if\ T_{used} > T_{\text{expected}}, \\ satisfaction_{QualityOfMedia}, & Otherwise \end{cases}$$

In the equation, $T_{expected}$ denotes the maximum available deliver time (*DT*) and T_{used} denotes the actual time spent delivering this adapted media version (n_i) transcoded by MP_i. The CAP algorithm is described in Algorithm *CAPAlgo*.

Example 5.5:

Given an Σ = {c_1, c_2} $\cup$ {1, 1000, 448, **480**, **800**, **24**, 16, 140} $\cup$ {1, **GPJB**, 1, 0} $\cup$ {500}**.** First of all, CAP retrieves the most appropriate page-level node n_p whose concept properties are the most similar to Σ (**Step 1**). Assume F_p = { c_1, c_2}, too. Assume there are two media-level nodes, n_1 is an image and n_2 is an audio file, in requested block-level node, where MP_1= {800, 400, 16, J, image, 160} without a corresponding physical adapted media file in the LOR. Therefore, the $content_1$ will be added into $\boldsymbol{Media_{req}}$ only due to the Audio Switch (AS) is 0, i.e., $\boldsymbol{Media_{req}}$ ={$content_1$} **(Step 2)**. Then, all MP_i of $content_i$ in $\boldsymbol{Media_{req}}$ will be inserted into $\boldsymbol{MP_{candi}}$ for calculating the *satisfaction score*. Thus, the $\boldsymbol{MP_{candi}}$ ={MP_1} **(Step 3)**. Afterwards, we can estimate the $\boldsymbol{T_{expected}}$**= 1/1=1** to understand how much time we can use to do the CAP for each requested $content_i$ **(Step 4)**.

For each $MP_i \in MP_{candi}$, we estimate how much time we need to spend delivering the media size over the Bandwidth (*b*) of the wireless network, i.e., $\boldsymbol{T_{deliver}}$ = 160 / 500 = 0.32 sec.; and how high the $\boldsymbol{Satisfaction_{QualityOfMedia}}$ is, i.e., $\mathbf{Sat_1}$ = 0.463, as described in Example 4. Then, because MP_1 has no corresponding physical media file in the LOR, the nearest physical media-level node, whose features are {1000, 500, 16, J, image, 160}, in the Media Version Base will be selected to estimate its transcoding time in advance if we deliver it to the user. Here, we can assume $\boldsymbol{T_{transcoding}}$=1 second. Therefore, the satisfaction score of MP_1 can thus be calculated by:

$$SatisfactionScore_{MP}(0.463,1,0.32+1) = \frac{0.463}{1+(1.32-1)/1} = 0.35$$ **(Step 5)**

Finally, if the MP_1 has the maximum satisfaction score in terms of $content_1$, it will be selected to insert into MP_{set}, which will be used to perform the learning content synthesis, as described in the follows **(Steps 6 and 7)**.

Algorithm 5.2: Content Adaptation Process Algorithm (*CAPAlgo*)

Symbol Definition:

∑: denotes a learner request, i.e., $\sum = CP_i \cup HP_i \cup LP_i \cup \{b_i\}$.

***content$_i$*:** denotes a original content of media-level node n_i.

***MP$_{candi}$*:** the candidate *MP* list

***Media$_{req}$*:** the set of requested media-level contents

MP$_{set}$ $= \{MP_1, MP_2,.., MP_k\}$: stores all appropriated *MP*s selected by *CAPAlgo*.

Sat$_i$: the $\text{Satisfaction}_{\text{QualityOfMedia}}$ of MP_i

T_{MDT}: maximum available delivery time, default is $DT \in LP$ in ∑

$T_{expected}$:the average expected time of deivering each requested media-level nodes.

$T_{deliver}$: the estimated deliver time of the n_i.

$T_{transcoding}$: the estimated transcoding time of the n_i.

Input: a ∑, T_{MDT}

Output: MP_{set}

Step 1: Select a page-level node n_p which has the highest $\text{Satisfaction}_{\text{Page}}(\sum, F_p)$ among all page-level nodes. Let n_i be the block-level nodes of n_p where $n_i \in child_p$.

Step 2: add all requested media-level contents (*contents*) into $Media_{req}$

Step 3: for each $content_i \in Media_{req}$, add all $MP_j \in f_j$ where $content_j = content_i$ into MP_{candi}

Step 4: calculate $T_{expected} = T_{MDT}$/(the number of $content_i$ in $Media_{req}$)

Step 5: for each $MP_i \in MP_{candi}$

5.1: Calculate $\text{Sat}_i = \text{Satisfaction}_{\text{QualityOfMedia}}(\sum, \text{MP}_i)$

5.2: Calculate $T_{deliver}$= size (S)$\in MP_i$ / Bandwidth(b)$\in$ ∑

5.3: Calculate

$$T_{transcoding} = \begin{cases} 0, \text{if physical file of } n_i \text{ is in Learning Object Repository (LOR)} \\ \text{Estimate transcoding time from nearest physical file in LOR} \end{cases}$$

5.4: Calculate Satisfaction Score of $\text{MP}_i = \text{SatisfactionScore}_{\text{MP}}(\text{Sat}_i, T_{\text{expected}}, T_{\text{deliver}} + T_{\text{transcoding}})$

Step 6: for each $content_i \in Media_{req}$,

6.1: Select MP_i with maximum Satisfaction Score and store it into MP_{set}.

Step 7: Return the MP_{set}.

5.3.3 Content Version Reuse Decision

The Content Adaptation Decision Tree (CADT) can be used to search, retrieve, and maintain block-level nodes. The desired adapted contents can be delivered quickly to learners if there is a similar existing case held by CADT. Determining how to efficiently deliver an appropriate adapted content from the existing block-level nodes or how to redo the aforementioned Content Adaptation Process (CAP) is a concern. We propose an **Adaptation Decision Process Algorithm** (ADPAlgo) to process the adapted content decision quickly. The ADPAlgo is shown as follows.

In the Adaptation Decision Process (ADP), we are given a new $\sum = CP_x \cup HP_x \cup LP_x \cup \{b_x\}$. First, a suitable page-level node is selected by using the concept properties CP and all the required content $content_x$ are determined. Second, a cluster will be selected by traversing the CADT based on $\mathrm{HP_x}$ and these block-level nodes n_i, whose features $F_i = HP_i \cup LP_i \cup \{b_i\}$ in the selected cluster will be merged with those in the Block Version Base. Third, a block-level node will be deleted if it satisfies one of four selection rules, e.g., $content_x \neq content_i$. Fourth, if there is a remaining nodes with higher similarity compared to the $\sum$, the Learning Content Synthesizer (LCS) will compose the personalized learning content and transcode the associated contents based on necessity. Then, the adapted learning content will be delivered to a learner directly without or with low transcoding latency. Otherwise, the block-level nodes will be triggered to create a new block-level node based on the $\sum$.

Example 5.6:

Based on the data in Table 5.1, given a new Learner Request $\sum = CP_x \cup HP_x \cup LP_x \cup \{b_x\}$

= {c_1, c_2} ∪ {**2**, 528, 384, 320, 480, **24**, 32, 120} ∪ {5,JGBP,1,1} ∪ {90} and a new n_{16} = ({1, 133, 128, 480, 640, 16, 16, 44} ∪ {12, GJBP, 0, 1} ∪ {150}, $child_i$, *1*, $content_i$) in the **Block Version Base**. By using CP_x, the most suitable page-level node is selected and the inner $content_x$ will be retrieved by using Adaptation Decision Process Algorithm (ADPAlgo). According to the CADT in Figure 5.3, we can find the rule: ***if*** *Machine Type* (MT) = '2' ***and*** *Color Depth* (CD) = '24,' ***then*** '**C_2**,' so that we can use the block-level nodes {n_2, n_5, n_7, n_9, n_{11}, n_{12}, n_{13}, n_{15}} of C_2 in Table 5.2 and n_{16} in **Block Version Base** to select a suitable block-level node (**Steps 1 and 2**). Then, n_{16} is deleted due to ($content_i \neq content_x$), and n_2, n_5, n_7, n_{11}, n_{12}, and n_{13} are deleted due to their bandwidth deviation ≧ 45 **(α×B)** while **α** is 0.5 and $\boldsymbol{b_i}$ is 90 KB **(Step 3 through Step 4**). Afterward, n_{15} with n_7 similar attributes while S_{min}=0.9(β)×8(N_{HP})=7.2 and the similarity value = 0.772 (>γ=0.6) compared with an ∑ is a suitable n_i for the user **(Step 5 through Step 6**).

However, because n_{15} is not completely the same as the ∑, a new node, n_{17}, will be created by the Content Adaptation Process (CAP) based on the ∑ and stored in the Block Version Base for the next similar learner request (**Step 8)**. Thus, the Block Version Base will hold two new nodes, i.e., {n_{16} and n_{17}} and the adapted Block Version Based on n_{15} will be delivered to a learner directly. Because the content version of n_{15} was adapted according to the previous similar learner request, the CAP process does not need to be executed again. Therefore, the adaptation and transcoding latency can be omitted and saved.

Algorithm 5.3: Adaptation Decision Process Algorithm (*ADPAlgo*)

Symbol Definition:

n_{set}: stores several historical blocl-level nodes

$content_x$: denotes the retrieved content in the selected page-level node.

$\sum$: denotes a learner request, i.e., $\sum = CP_x \cup HP_x \cup LP_x \cup \{b_x\}$.

n_{new}: stores the new block-level node created according to the $\sum$.

α: denotes the acceptable percent threshold of bandwidth deviation.

β: denotes the acceptable weight Threshold of the amount (N_{HP}) of attributes in *HP*.

γ: denotes the acceptable threshold of Similarity value.

$S_{Min} = \beta \times N_{HP}$: denotes the minimum amount of the same attributes value between HP_i and HP_x.

Input: a $\sum$, a $content_x$

Output: a suitable block-level node

Step 1: If the **CADT** is not Empty,

Then use the HP_x in $\sum$ to traverse the CADT for finding the suitable cluster with similar *HP*.

Step 2: Insert nodes n_i into n_{set} from the selected Cluster in CADT and **Block Version Base**.

Step 3: Delete these n_i from n_{set}, if $content_i \neq content_x$.

Step 4: Delete these n_i from n_{set}, if $|b_i - b_x| \geqq \alpha \times b_x$.

Step 5: Delete these n_i from n_{set}, if the number of HP_i attributes with similar value compared with $\sum < S_{Min}$.

Step 6: Delete these n_i from n_{set}, if the similarity between n_i in n_{set} and $\sum$ according to the **Similarity_{LP}**$(LP_x, LP_i) < \gamma$.

Stept 7: If $\exists$ a $n_i \in n_{set}$ whose attribute values in terns of HP_i and LP_i is the same as $\sum$,

Then goto Step 9.

Stept 8: do the Content Adaptation Process (CAP) according to the LP_x in $\sum$ and create the n_{new}

stored in Block Version Base.

Stept 9: If n_{set} is not empty,

Then Output the n_i with the highest similarity in n_{set}.

Else Output the n_{new}.

5.3.4 Content Adaptation and Synthesis

The Learning Content Synthesizer (LCS) aims to compose appropriate personalized learning content based on diverse learner preferences. As stated previously, when dealing with a new ∑ without any suitable existing adapted content to be delivered, the CAP will decide a corresponding $\boldsymbol{MP_{set}}$ to transcode the associated media resources. Hence, given that a page has n media resources and its corresponding $\boldsymbol{MP_{set}} = \{MP_1, MP_2, \ldots, MP_m\}$, where $1 \leqq m \leqq n$, it is implied that the (n-m) resources do not need to be transcoded and shown due to the satisfaction degree and Switch Attribute (SA) of media, e.g., **PS** and **AS** in the *LP*. To notify users, media resources that are not shown will be automatically replaced by some additional annotations from the SCORM metadata. To efficiently manipulate the diverse versions of learning content, a page's original HTML will be transformed into a well-formed XHTML and tree-like Document Object Model (DOM) structure. The details of the LCS are described in *LCSAlgo*.

Algorithm 5.4: Learning Content Synthesis Algorithm (LCSAlgo)

Symbol Definition:

$\mathbf{T_{CAP}}$**:** the spending time of executing the Content Adaptation Process (CAP).

$\mathbf{T_{ADP}}$**:** the spending time of executing the Adaptation Decision Process (ADP).

$\mathbf{T_{deliver}}$: the estimated deliver time of the media version (V) in MP_i.

$\mathbf{T_{score}}$**:** the minimum threshold of Satisfaction for the content adaptation process.

$\mathbf{T_{used}}$**:** The used time of *MP*s, which needn't be re-adapted.

DT: the maximum available delivery time, DT ∊ *LP* in ∑.

$\boldsymbol{Content_x}$**:** denotes a requested media-level content.

$\boldsymbol{MP_{set}} = \{MP_1, MP_2, .., MP_k\}$: stores all appropriated *MP*s selected by *CAPAlgo*.

$\boldsymbol{Media_{adapt}}$: store the media objects, which need to do content adaptation process

$\boldsymbol{r_\gamma}$ **:** denotes the original media resource in a page.

$\boldsymbol{Tr_\gamma}$ **:** denotes the transcoded media resource.

Input: a ∑ with corresponding $\boldsymbol{MP_{set}}$ and $content_x$.

Output: an adapted and transcoded learning content version, XHTML.

Step 1: if (n_i = ADPAlgo($\sum$, $content_x$)) = null**,**

Then

1.1: Estimate the T_{CAP} and T_{ADP}

1.2: MP_{set} =CAPAlgo($\sum$, DT-(T_{CAP}+ T_{ADP})), where $\mathbf{T_{MDT}}$ in CAPAlgo = (DT-(T_{CAP}+ T_{ADP})).

Else

1.3: for each $MP_i \in MP_{set}$ in n_i

1.3.1: Calculate Sat_i= $Satisfaction_{QualityOfMedia}(\sum, MP_i)$

1.3.2: Calculate $\mathbf{T_{deliver}}$= size ($size_i$) / Bandwidth(b_x)$\in \sum$

1.3.3: Calculate $T_{transcoding}$=

$$\begin{cases} 0, \textit{if physical file of } MP_i \textit{ is in Learning Object Repository (LOR)} \\ \textit{Estimate transcoding time from nearest physical file in LOR} \end{cases}$$

1.3.4: Calculate Satisfaction Score of MP_i

= ***SatisfactionScore$_{MP}$***(Sat_i, DT/(the number of $MP_i \in MP_{set}$), $T_{deliver}$+ $T_{transcoding}$)

1.3.5: If Satisfaction Score of MP_i < T_{score}, then add $content_i$ of MP_i into ***Media$_{adapt}$***

1.4: Estimate the T_{CAP} and T_{ADP}

1.5: for each $MP_i \in MP_{set}$ and $\notin$ $Media_{adapt}$,

1.5.1: Calculate T_{used} = $T_{deliver}$+ $T_{transcoding}$

1.6: for each $content_k \in Media_{adapt}$,

1.6.1: the MP_i of $content_k$ =CAPAlgo($\sum$, DT-(T_{CAP}+ T_{ADP}+ T_{used})),

where $\mathbf{Media_{req}}$ in CAPAlgo **=** $\mathbf{Media_{adapt}}$ and

$\mathbf{T_{MDT}}$ in *CAPAlgo* **=(** DT-(T_{CAP}+ T_{ADP}+ T_{used})).

1.6.2: replace the original media-level nodes.

Step 2: for each media resource, r_γ, in a page**.**

2.1: apply $\mathbf{MP_\gamma \in MP_{set}}$, to transcode the r_γ into the tr_γ.

Step 3: transform the original HTML into XHTML format

Step 4: replace all r_γ by tr_γ into the XHTML**.**

Step 5: replace all unshown media resources by the useful annotation from SCORM metadata.

Step 6: output the XHTML with associated transcoded media resources.

Example 5.7:

Assume the CADT structure has already been built. Then, given $\sum = \{c_1, c_2\} \cup \{1, 1000, 448, 480, 800, 24, 16, 140\} \cup \{1, GPJB, 1, 0\} \cup \{500\}$ and the minimum threshold of satisfaction, T_{score} = 0.7. After the ADPAlgo (∑) process, there are two media-level nodes with the corresponding *MPs* in MP_{set}, i.e., MP_{set}={MP_1, MP_2}={("M_{1v0}", image, <800, 400, 16, J>, 160), ("M_{2v1}", image, <480, 700, 24, P>, 50)}. Thus, assume $\mathbf{T_{ADP}}$ =1 sec., and $\mathbf{T_{deliver}}$ of MP_1= (size in MP_1)/ (bandwidth in LR) = 160 KB / 500 KB=0.32 sec. and $\mathbf{T_{deliver}}$ of MP_2= 50 KB/ 500 KB=0.1 sec. **(Step 1.3.b)**. The associated Media Object, *content*$_2$, of MP_2 does not need to be adapted again because *content*$_2$ has the adapted media version (**V_1**) based on MP_2, i.e., M_{2v1}, in the LOR. On the contrary, M_{1v0}, which is the original version (V_0) of MO_1, must be adapted according to the definition of MP_1 before it can be delivered to the learner. Therefore, assume $\mathbf{T_{transcoding}}$ = 1 sec. to adapt M_{1v0} into the nearest version, i.e., ("M_{1v2}," image, <800, 400, 16, B>, 500) **(Step 1.3.c)**.

In addition, according to the result of Example 5.4, the $\mathbf{Sat_1}$ of MP_1 is 0.463 by the equation: $\boldsymbol{Satisfaction_{QualityOfMedia}}$(∑,$MP_1$) **(Step 1.3.a)**. Consequently, the satisfaction score of MP_1 is calculated by:

$$SatisfactionScore_{MP}(0.463,1,0.32+1) = \frac{0.463}{1+(1.32-1)/1} = 0.35$$

Besides, $\mathbf{Sat_2}$ is calculated by:

$Satisfaction_{QualityOfMedia}(\Sigma, MP_2) = 0.5 \times SimofNum(480 \in HP, 480)$

$+ 0.1 \times \boldsymbol{SimofNum}(800 \in HP, 700) + 0.3 \times \boldsymbol{SimofNum}(24 \in HP, 24)$

$+ 0.1 \times \boldsymbol{SimofImage_{Type}}(\text{"GPJB"} \in LP, \text{'P'}) = 0.9625$ **(Step 1.3.1)**

Consequently, the satisfaction scores of MP_2 is calculated by:

$\boldsymbol{SatisfactionScore_{MP}}(0.9625,\ 2\ /\ 2\ ,\ 0.1\ +\ 0)\ =\ \dfrac{0.9625}{1+(0.1-1)/1} = 0.9625$, because the $\boldsymbol{T_{transcoding}}$ = 0 sec. for adapting M_{2v1} **(Step 1.3.2)**.

Because the satisfaction score of MP_1 = 0.35, which is less than 0.7 (T_{score}), and the satisfaction score of MP_2 = 0.9625, which is larger than 0.7, the MO of MP_1, M_{1v0}, will be added to the $Media_{adapt}$ for further adaptation process, i.e., $\mathbf{Media_{adapt}}$ ={"M_{1v0}"} **(Step 1.3.5)**.

Assume $\mathbf{T_{CAP}}$ = 0.2 sec. and $\mathbf{T_{ADP}}$ = 1 sec. for the "M_{1v0}" **(Step 1.4)**, "M_{2v1}" of MP_2 doesn't need to be adapted again, so the $\mathbf{T_{used}}$ for MP_2 = $T_{deliver}$+ $T_{transcoding}$=0.1+0=0.1 **(Step 1.5).** Afterward, we can get an MP_3=("$M_{1v0,}$" image, <480, 240, 24, P>, 20) for the "M_{1v0}" by calling the CAPAlgo(Σ, T_{MDT}) = CAPAlgo(Σ, DT-(T_{CAP}+ T_{ADP}+ T_{save})) = CAPAlgo(Σ, 2-(0.2+ 1+ 0.1)), where $\mathbf{Media_{req}}$ in CAPAlgo = $\mathbf{Media_{adapt}}$ = {$content_1$} **(Step 1.6.1)**. Therefore, MP_{set}={MP_3, MP_2}={("$M_{1v0,}$" image, <480, 240, 24, P>, 20), ("$M_{2v1,}$" image, <480, 700, 24, P>, 50)} **(Step 1.6.2)**. According to the MP_{set}, the media version, M_{1v0}, of MP_3 will be transcoded by the definition of MP_3 first, and then output the XHTML with associated transcoded media resources **(Step 2 through Step 6)**.

5.4 Experimental Result

A Personalized Learning Content Adaptation Model (PLCAM) system [85] based on MGC model was constructed to evaluate the effectiveness of MGC model, and actual experiments and simulated experiments were performed. The details and results are described in the following sub-chapters.

5.4.1 Result of Actual Experiments

In the actual experiments, performance of the prototypical PLCAM system was evaluated by the experimenters in terms of the personalized learning content delivering process, including the Content Adaptation Process (CAP), the Adaptation Decision Process (ADP), and the Learning Content Synthesizer (LCS), and the dynamic bandwidth detection scheme, based on the SCORM-compliant learning content in relation to "the plants in campus". These characteristics were tested to observe and evaluate the resultant Delivery Time (*DT*) and the transmission data size according to various bandwidth settings for different requests. The performance of the PLCAM in terms of DT compared with inadaptation and static adaptation approaches was evaluated as well.

As mentioned in Sections 5.1 and 5.2, the *DT* plays an important role in affecting one's learning performance in mobile learning environments. Therefore, a bandwidth detection scheme was developed to automatically detect the latest network bandwidth for providing the learner with more precise personalized learning content with higher fidelity. As shown in Figure 5.5.a, with the decrease of "actual" network bandwidth, the bandwidth that a user can consume will decrease as well by means of monitoring each transmission time compared with the setting of the user's desired maximum DT. For example, in Figure 5.5.b, a user's functional bandwidth has been updated at 3, 5, and 7 (times) due to the detection of the long delivery latency at 2, 4, and 6 (times) (maximum *DT* = 5 sec.).

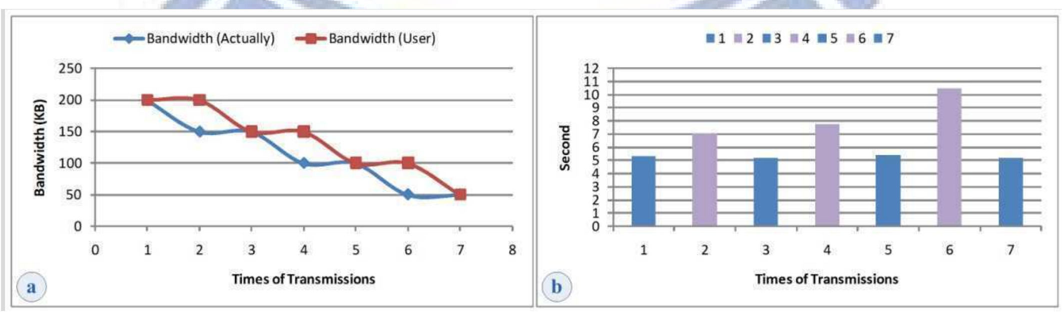


Figure 5.5: Experiment results of the automatic dynamic bandwidth detection scheme

Figure 5.6 shows the effectiveness of the PLCAM in delivering proper personalized adapted learning content that meets a similar $\sum$ without waiting for the CAP to be completed.

Therefore, Fig. 11 illustrates the *DT*, which consists of the data transmission time and the PLCAM adaptation time, in terms of the different requests and the size of transmission data based on the various bandwidth settings. In Figure 5.6.a, assume the definition of the maximum *DT* is 5 sec., during the first request for a learning object, the average *DT* is about 8.416 sec., including the content adaptation process (about 3 sec.) and the actual content delivery. On the contrary, the average *DT* during the second request can be controlled around 5.238 sec. to meet the constraint of the maximum *DT* without repeating the content adaptation process. Figure 5.6.b shows that the size and quality of transmission data can be increased gradually with the increase of usable bandwidth by the aforementioned dynamic bandwidth detection scheme based on the definition of maximum *DT*.

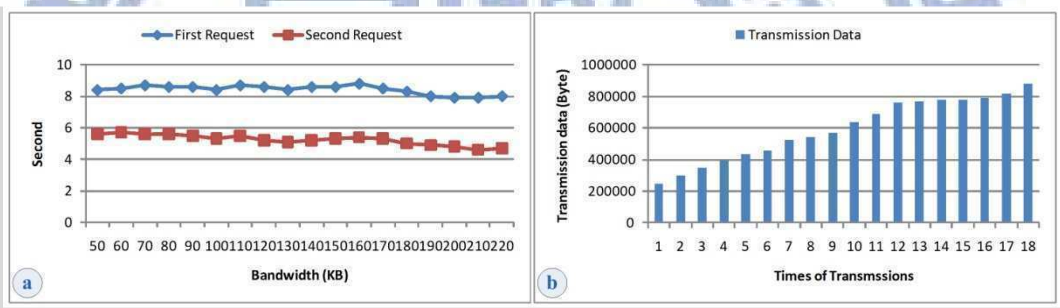


Figure 5.6: DT of different requests and transmission data size based on various bandwidth settings

Assumed that there is a learning object, which contains a Waveform Audio Format (WAV) file with 660,768 bytes and six pictures with 1,016,392 bytes. The original size is about 1.8 Mbytes. The learner specified the maximum tolerable *DT* to be 5 sec. We observed the transmission results based on the various bandwidth settings in terms of the approaches, which included the inadaptation, static adaptation, and PLCAM. In Figure 5.7, the inadaptation approach transmits content without employing the content adaptation process and spends much more *DT* than the static adaptation approach and the PLCAM. In this example, the static adaptation approach prepared three versions of learning content in advance, i.e., 200 KB, 170 KB, and 140 KB. Therefore, within the bandwidth range from 140 KB to 220 KB, the *DT* is almost the same between the static adaptation approach and the PLCAM. However, the static adaptation approach cannot consistently provide users with the appropriate content version according to the various bandwidths; thus, this approach spent a great deal of time gradually decreasing the bandwidth from 140 KB to 50 KB. On the contrary, the PLCAM is still able to offer a stable delivery time and the proper personalized adapted content to meet the diverse user needs.

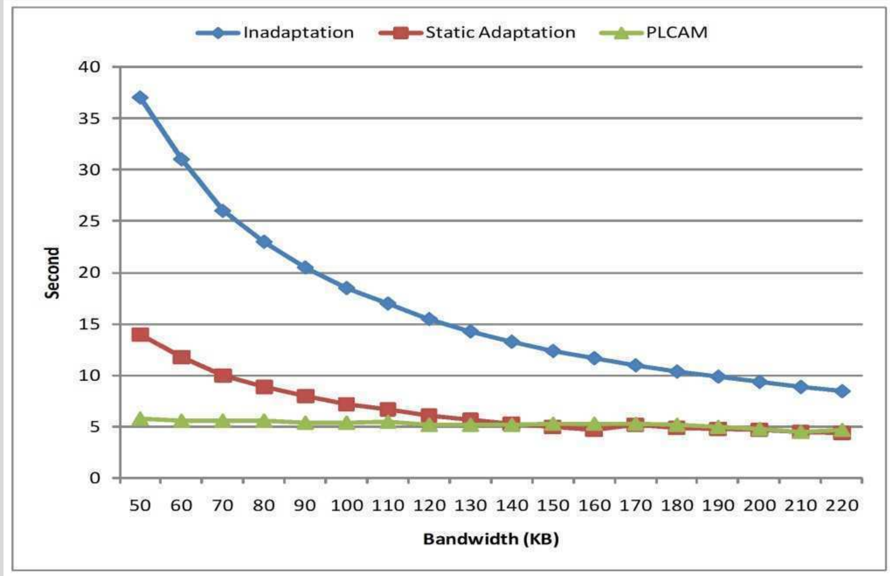


Figure 5.7: Comparison among the inadaptation, static adaptation, and PLCAM approaches

5.4.2 Results of Simulated Experiments

To evaluate the performance and effectiveness of the PLCAM in depth, several simulated experiments were carried out, emulating a large number of diverse user requests with Learner Preferences (LPs) and Hardware Profiles (HPs) to access the desired Learning Objects from the Learning Object Repository (LOR). The performance and satisfaction degree of the PLCAM in terms of: 1) Learning Content Adaptation Management Scheme (LCAMS) with Content Version Cluster Decision Tree (CADT) in Figure 5.8, Figure 5.9, Figure 5.10, and Figure 5.11; 2) the parameter setting of the LP clustering algorithm in Figure 5.12; and 3) the CADT maintenance process in Figure 5.13 and Figure 5.14 were evaluated based on the different experimental conditions, including bandwidth, LPs, and devices.

The simulated experiments were executed on a computer with a 1-GHz Central Processing Unit (CPU), 1 G of Random Access Memory (RAM), and a Windows XP Operating System (OS). Table 5.5 lists the HP data used to perform the following experiments.

Table 5.5: HP in ∑ data used for the simulation experiments

ID	HP in CAR	Machine Type
1	<**2**, 600, 384, 320, 480, 24, 16, 40>	Cell Phone
2	<**1**, 1000, 576, 480, 800, 24, 32, 100>	PDA
3	<**1**, 1000, 448, 480, 800, 24, 16, 140>	PDA
4	<**2**, 528, 288, 320, 480, 32, 8, 20>	Cell Phone
5	<**2**, 528, 384, 320, 480, 16, 32, 120>	Cell Phone
6	<**2**, 528, 288, 320, 480, 16, 8, 30>	Cell Phone
7	< **0**, 2000, 8000, 1366, 768, 32, 32, 500>	Notebook
8	<**0**, 1200, 4000, 1366, 768, 32, 16, 300>	Notebook

The LCAMS in the PLCAM uses the CADT structure to efficiently determine the appropriate personalized learning content to meet the diverse learner requests. Therefore, we analyzed the performance and differences between the PLCAM without and with the CADT to perform the content adaptation based on different bandwidths, 5000 KB, 2000 KB, 1000 KB, 500 KB, 250 KB, 50 KB, and the number of requested Media Objects (MOs) from 1 to 15, i.e., [1-15]. During this simulated experiment, each of the 250 Learner Requests (∑s) was generated by LP=(Maximum Delivery Time=1 sec., JPBG, 1/0, 1/0) and the random HP ID between 1 and 6, i.e., [1,6], in Table 5. The results of the simulated experiment are shown in Figure 5.8 and Figure 5.10, respectively.

In Figure 5.8, the Query-Diff and Sat-Diff denote the difference of query time of determining the suitable MP_{set} and the satisfaction score between the PLCAM without and with the CADT, respectively. Figure 5.8.a shows that the Query-Diff explicitly increases with the increase of bandwidth $\geqq$ 250 KB and the number of requested MOs $\geqq$ 4, which shows that the

CADT can efficiently speed up the performance of the Adaptation Decision Process (ADP).

Figure 5.8.b indicates that the Sat-Diff also increases if the bandwidth ≧ 500 KB and the number of requested MOs ≧ 7, which shows that decrease of query time can enhance the satisfaction score because response time is an important factor in user satisfaction. As for the bandwidth = 50 KB, the Sat-Diff and Query-Diff are very low because the available DT is insufficient to determine the MP_{set} with a better satisfaction score in the ADP. On the contrary, the PLCAM without the CADT needs much more time to determine the suitable MP_{set} from the MP database while the number of requested MOs increases.

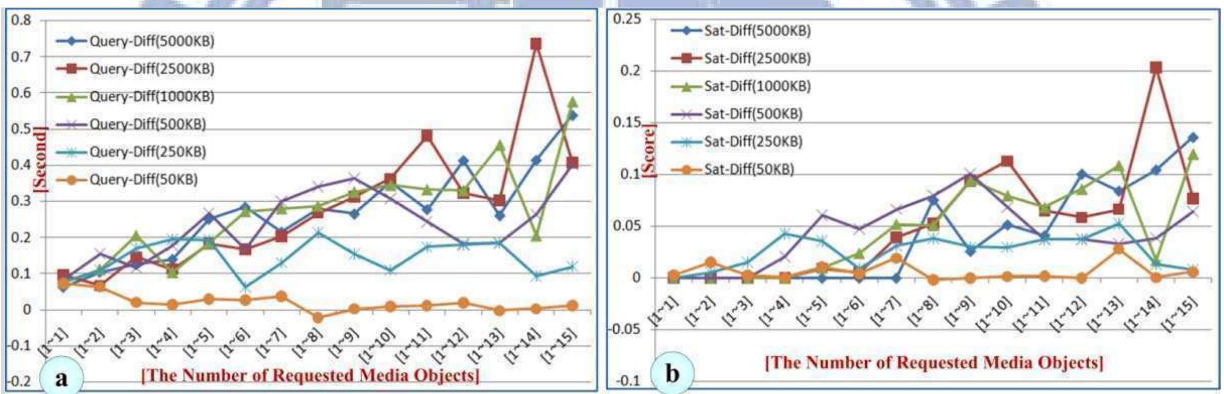


Figure 5.8: Comparison of (a) the difference of query time; and (b) the difference of satisfaction between the PLCAM without and with the CADT based on different bandwidths and requested MOs

Figure 5.9 shows the delivery time, the query time, and the satisfaction score between the PLCAM without and with the CADT based on 500 KB bandwidth only. In Figure 5.9.a, the Delivery Time (CADT), consisting of physical data transmission time and transcoding time, is almost the same as the PLCAM without CADT approach. In Figure 5.9.b, the difference of query time (Query-Diff) is from 0.08 sec. to 0.4 sec, which saves 8 to 40 percent time consumption in terms of DT=1 sec. Furthermore, although the PLCAM uses the CADT to improve the performance of the content adaptation process, a higher satisfaction score than the score obtained without the CADT, can be maintained, as seen in Figure 5.9.c.

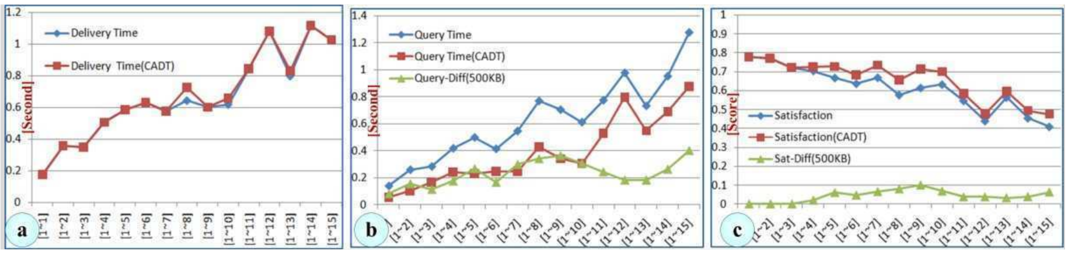


Figure 5.9: Comparison of (a) the delivery time; (b) the query time; and (c) the satisfaction score between the PLCAM without and with CADT based on 500 KB bandwidth and different requested MOs

Regarding the influence of bandwidth between query time and the satisfaction score, Figure 5.10.a shows that the average DT is almost the same without and with the CADT. This finding indicates that the CADT can determine similar personalized learning content like the PLCAM without CADT. Also, query time (CADT) will decrease with the increase of bandwidth, while query time without the CADT is almost the same, as seen in Figure 5.10.b. This is a 2 to 27 percent (average 20 percent) time consumption savings in terms of DT=1 sec. Therefore, the average satisfaction score (CADT) is also better than “without CADT,” as presented in Figure 5.10.c.

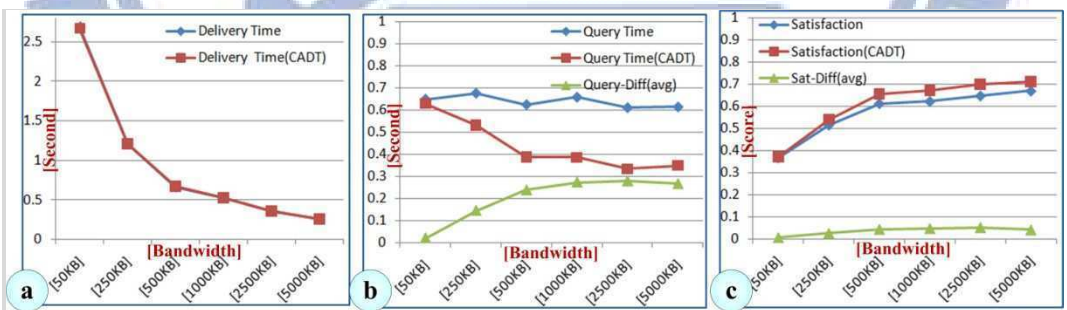


Figure 5.10: Comparison of (a) the average delivery time; (b) the average query time; and (c) the average satisfaction score between the PLCAM without and with the CADT based on different bandwidths and requested MOs

To evaluate the performance of the PLCAM in actual mobile learning environments, we emulated diverse LRs actually used by the PLCAM with randomized LRs, which had random maximum DT between 1 and 8 sec., [1,8], the random bandwidths between 50 KB and 500 KB, [50 KB, 500 KB], and the random number of requested MOs between 1 and 9, [1,9]. We tested this simulated experiment for eight iterations, each of which used eight participant HP data in Table 5 and generated 250 LRs to test the PLCAM system. Fig. 16 shows the results of the experiment. The Delivery Time (CADT) is a bit higher than what is seen without the CADT, as shown in Figure 5.11.a. The Query Time (CADT) is still better than what is observed without CADT, from about 0.15 to 0.27 sec. (average is 0.2 sec.), as seen in Figure 5.11.b, and the satisfaction score is almost the same and stable around 0.7 during eight iterations. These results show that the PLCAM with the CADT can achieve better and more stable performance regarding learning content adaptation and the satisfaction degree in simulated actual learning environments.

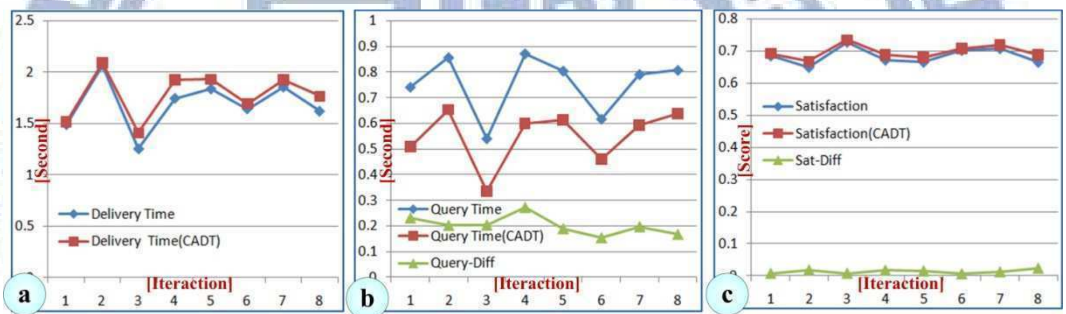


Figure 5.11: Comparison of (a) the delivery time; (b) the query time; and (c) the satisfaction score between the PLCAM without and with the CADT on random bandwidths [50 KB, 500 KB], random maximum DT [1,8], random requested MOs [1,9], and eight HP data points in Table 5

To analyze the parameter setting of the Content Version Clustering Algorithm (***CVClustering***), we used different parameter settings to test the satisfaction score of the PLCAM system based on LP=(1, JPBG, 1/0, 1/0), HP from 1 to 6 in Table 5.5, bandwidth=500 KB, and the number of MOs between 1 and 9. The parameter setting of the ***CVClustering*** has been found as {K=3, T_s=0.004, T_m=2, T_n=3, T_p=2}, where the PLCAM attains a better satisfaction degree.

By means of the analysis of the parameter setting of ***CVClustering***, we found that the number of block-level nodes in the Block Version Base, employed to be the threshold of rebuilding the CADT, play an important role in satisfaction. Therefore, we used the aforementioned parameter setting to evaluate the performance of the PLCAM system by adjusting the threshold of rebuilding the CADT. Thus, the experimental results are shown in Figure 5.12, where we find that the most suitable thresholds to rebuild the CADT are: 5 at 250 requests, 35 at 500 requests, and 45 at 1000 requests, respectively. According to these results, we can use the ordinary least squares approach to estimate the CADT rebuilding equation:

CADT Rebuilding Equation: $Y= 0.04857X$, where Y is the predicted thresholds of rebuilding the CADT and the X is the number of $\sum$s.

For example, if the number of $\sum$s is 750, we can use the $Y=0.04857X=0.04857\times750=36$ to be the threshold. Therefore, if there are 36 nodes in the Block Version Base and the total $\sum$s is larger than 750, the CADT maintenance process will rebuild the CADT automatically.

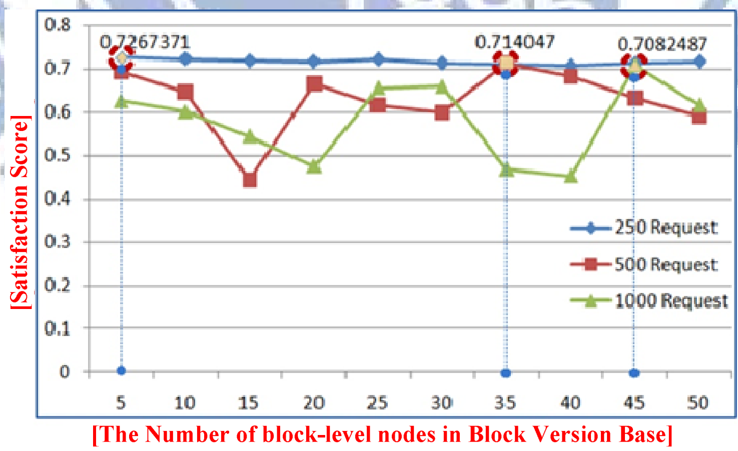


Figure 5.12: Most suitable threshold of rebuilding CADT based on the different amount of nodes in the Block Version Base

By means of the CADT rebuilding equation, the PLCAM can automatically maintain its CADT associated with historicalnodes according to the “use situation” of learners. Therefore, in order to evaluate the performance of the PLCAM with the CADT maintenance process, we test the PLCAM by LP=([1,8], random, 1/0, 1/0), Bandwidth=[50 KB,500 KB], the number of media=[1,9], the HP data in Table 5.1 to emulate the actual use by learners.

Figure 5.13 illustrates time spent during the transcoding process over the course of 1000 LRs. In Figure 5.13, most of the transcoding time was spent during the early phase of the requests, as opposed to the latter phase. Because the PLCAM can efficiently manage a large number of historical learners' requests and intelligently deliver proper personalized learning content with higher fidelity from the Media Version Base to the learner directly, the transcoding time can be decreased substantially.

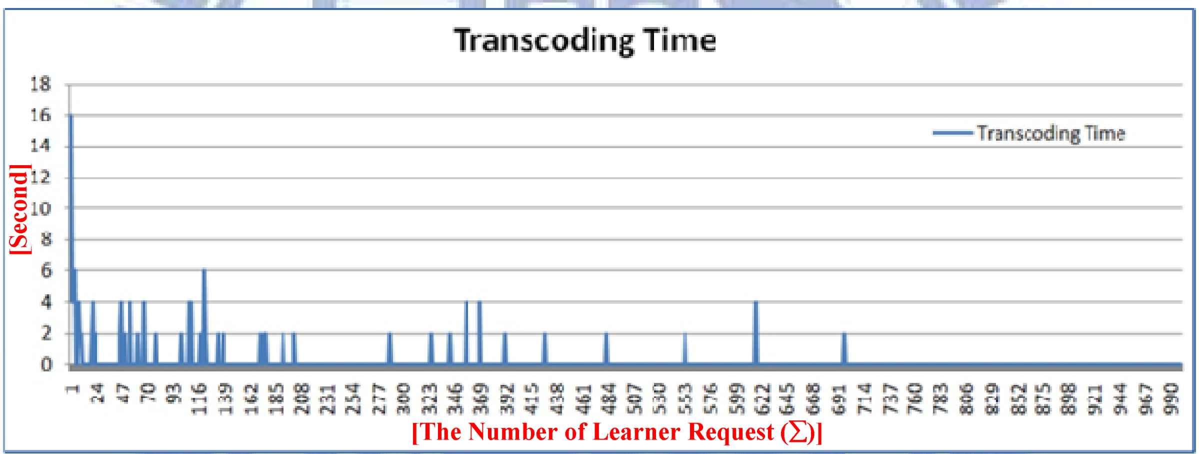


Figure 5.13: Resultant transcoding time of the PLCAM with auto-adjustment scheme

Figure 5.14 illustrates the comparison of query time and the satisfaction score of the PLCAM between the dynamic-threshold estimated by the CADT rebuilding equation and static-threshold based on the same experimental condition. According to Figure 5.14, we can find that the PLCAM with dynamic-threshold can outperform the one with static-threshold.

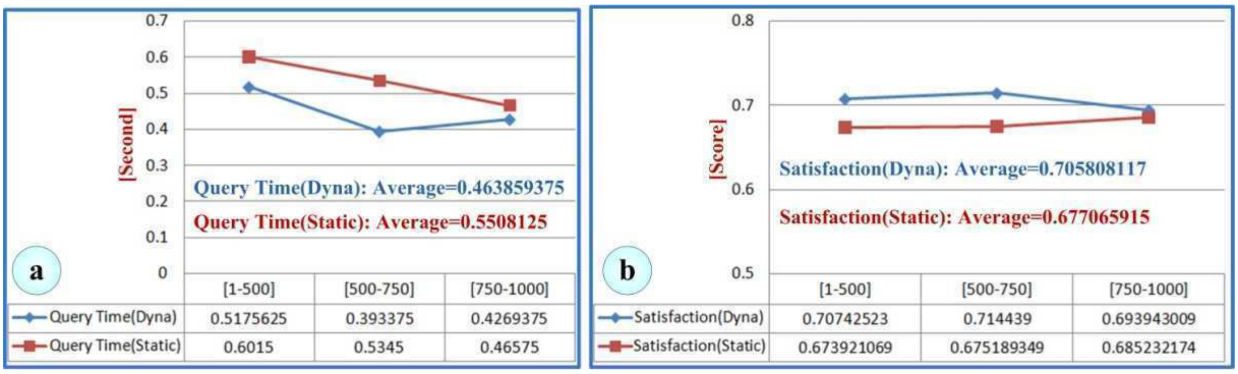


Figure 5.14: Comparison of (a) query time; and (b) the satisfaction score of the PLCAM between dynamic-threshold and static-threshold by the random LRs and eight HP data points in Table 5

According to the experiment described above, the result shows that CADT can really improve the efficiency of content adaptation, especially in the low-bandwidths environments. The assumption of this approach is that the attribute set used in the system is fixed. If the approach is used with a dynamic attribute set to more flexibly satisfy various learners needs, the multiple CADTs need to be generated and the meta-rules need to be used to determine the attribute set and the corresponding CADT.

Chapter 6 Heterogeneous Knowledge Diagnosis Model

To cope with the Process Skill Diagnosis Subproblem, a middle-level knowledge representation is needed to extract the learners' learning status from heterogenerous learning events and provide structural learner models for learning diagnosis. Thus, an **Ability-Centered Level** is defined to connect high-level diagnosis knowledge and low-level learning events, where all the learning behaviors and test results are structured for further diagnosis. In the Ability-Centered Level, the background knowledge, including concepts or process skills, is represented as the ontology, where concepts and skills are represented as nodes and the prerequisite relations and dependency relations are represented as the relations between nodes. Not only traditional test results but also learning and testing behaviors in virtual laboratories or simulation tests are extracted and represented as predicates of learning status [59]. For example, after learners get a score 0.8 of a concept c_1 in a test, a predicate is recorded as *Score*(c_1, 0.8), and after reading a lecture about c_1 during the inadequate reading time, the learning behavior is also be recorded as *LearningTime*(c_1, *inadequate*). Besides, assume a learner do a wrong operations about the measurement skill in the virtual lab, a predicate *WrongOperation*(*measurement*) is recorded. In order to extract the structured learning status from the learning events, the frame-based knowledge representation is used to model all the learning activities. For example, the frame of a reading activity records the lecture's expected reading time and its associated concepts. For an experiment-based test, the frame records all necessary and wrong operation patterns and their associated skills and concepts. The embedded rules are defined to transform a learner's learning events to the predicates in the Ability-Centered Level according to the slots of the frames. Besides, the high-level learning diagnosis knowledege can be represented by using rule-based representation, which can infer learning status and learning barriers from the predicate of learning status and the relations in the ontology of the Ability-Centered Layer.

6.1 Definition of Heterogeneous Knowledge Diagnosis Model

The definition of this Heterogeneous Knowledge Diagnosis Model (*HKD*) is as follows:

HKD = (*Ontology*, *F*, *DR*): Heterogeneous Knowledge Diagnosis Model.

Ontology : a set of ontology.

$F = \{f_1, f_2, \ldots, f_n\}$: a set of frames.

$f_i = (E_i, V_i, CR_\mathrm{i})$: a frame of learning activity.

$E_i = \{e_1, e_2, \ldots\}$ is a set of all learning events related to the activity.

V_i is a set of all slot values.

CR_i: $E_\mathrm{i} \times V_\mathrm{i} \rightarrow P$ is the learning status crystalization rule set, where P denotes the set of predicates of learning status

DR: $P \times Ontology \rightarrow \sum$ is the diagnostic rule set, where $\sum$ including a set of attributes, denotes the set of learner model.

6.2 Domain Ontology in Ability-Centered Level

In order to assess learners' experimental portfolios, the experiment knowledge related to the scientific inquiry experiment need to be defined in advance. Therefore, in the HKD, two kinds of knowledge structures are defined by the teacher: the concept map of a subject and the skill map of scientific inquiry. The former denotes necessary concepts that learners need to learn and understand, and the latter denotes the required skills learners need to be equipped with in this assessment experiment. The concept map and the skill map used in the *Ontology* of HKD are defined as follows, respectively.

Definition of the Concept Map (CM):

- CM=(C, R), where:
- $C = \{\mathrm{c}_1, \mathrm{c}_2, \ldots, \mathrm{c}_\mathrm{n}\}$: c_i represents the main concept in a subject
- $R = \{\mathrm{cr}_1, \mathrm{cr}_2, \ldots, \mathrm{cr}_\mathrm{m}\}$: cr_i represents the Relation Type between two concepts in a CM,

where the Relation Type is defined as the **APO:** c_i *is* ***A Part Of*** $c_{j,}$ or the **PR:** c_i *is the* ***Prerequisite*** *of* c_k.

Here, the CM, consisting of a set of concepts (c_i) with two types of relations, i.e., A-Part-Of relations (*APO*) and Prerequisite Relations (*PR*), is a hierarchical structure of concepts of a subject. By means of these relational definitions among concepts, learning problems related to subject concepts can thus be found and diagnosed for a learner. Figure 6.1 depicts an example of a partial CM of a Biology Transpiration Experiment, where the concept *Phenomenon* has three sub-concepts: *Transpiration*, *Photosynthesis*, and *Capillarity*, and prerequisite concepts of *transpiration* are *water transportation* and *Capillarity*.

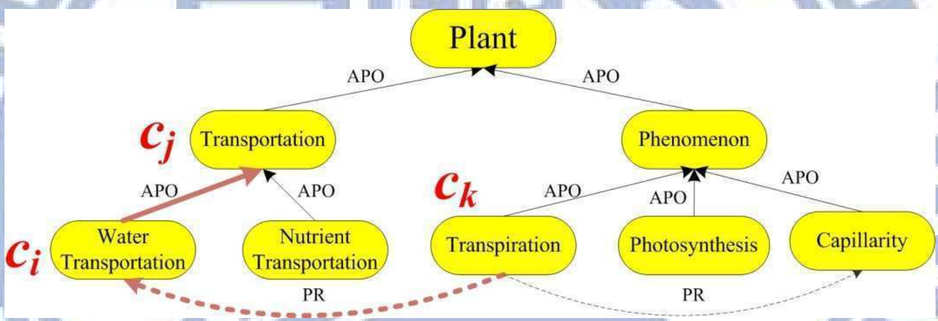


Figure 6.1: Example of a Partial CM of the Biology Transpiration Experiment

Definition of the Skill Map (SM) for Scientific Inquiry:

- ***SM***=(S, R), where:
- $S = \{s_1, s_2,..., s_n\}$: s_i represents a Skill of Scientific Inquiry Skills.
- $R = \{sr_1, sr_2,..., sr_m\}$: sri represents the Relation Type between two skills in a *SM*, where the Relation Type is defined as the **APO**: s_i is A Part Of s_j, or the **D**: s_i is Dependence on s_k.

The structure of the *SM* for scientific inquiry is the same as the *CM*, expect for cross-link relation definitions, Dependence Relations (D), which represent cause-and-effect relations between two skills. For example, Figure 6.2 illustrates an example of a partial SM for the scientific process, where the skill, *Setting Variables*, depends on the skill, *Making Hypothesis*.

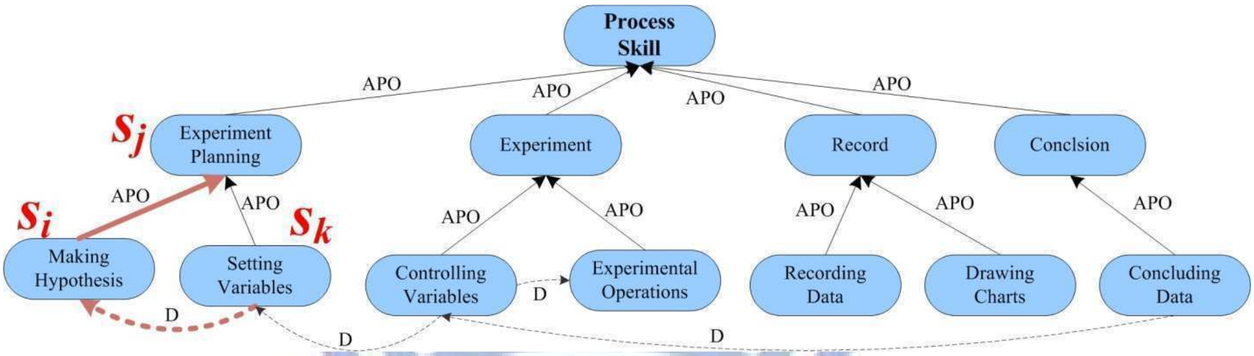


Figure 6.2: Example of a Partial Scientific Process Skill Map for the Scientific Inquiry Experiment

6.3 Learning Activity Frame

6.3.1 Key Operation Action Pattern

During the Web-based scientific inquiry experiment, learners will be asked to operate the Web-based operation experiment tool, which emulates the actual experiment operation, and their behavior will be collected and regarded as Operational Data of the scientific inquiry assessment portfolio. However, an important problem is how to automatically assess and evaluate operational data of learners. Therefore, in the HKD, the Key Operation Action Patterns (KOAP) has been proposed to evaluate the accuracy of learners' operational data. The KOAP defines key operational actions and sequences, which will influence the operational accuracy of the Web-based operation experiment tool. Accordingly, the teacher can define the necessary KOAP to observe and evaluate learners' operational data. The definitions related to the Experiment Operations (EO) and KOAP in terms of the Web-based operation experiment are defined as follows:

Definitions of the *EO*:

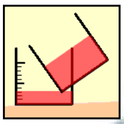
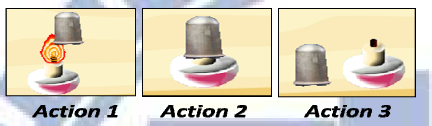
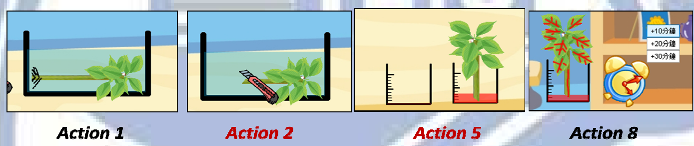
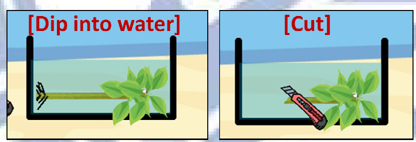
- ***EO*={a_1, a_2,…, a_n}**: denotes all actions that a learner can operate in terms of a Web-based operation experiment tool in the scientific inquiry assessment experiment.

Definitions of the KOAP:

- ***KOAP***=(KA, AC, AS, OC), where:
- ***KA*****={a_i, a_j,…, a_m |** 0≦the amount of KA≦n of ***EO*****}:** denotes the **Key Action (KA)**, each action (a_i) of which plays an **important action** of all operational actions in ***EO***, whose accuracy will influence the accuracy of the whole EO.
- ***AC*****=(a_i, a_{i+1}, a_{i+2},…):** denotes the **Action Continuity (AC)**, which is an action sequence with continuous actions.
- ***AS*****=(a_i, a_{i+j},…,a_{i+k} | i<j<k):** denotes the **Action Sequence (AS)**, which is an action sequence, but its continuity is not necessary.
- ***OC*****=(a_i, a_{i+1}, a_{i+2},…):** denotes the **Object Continuity (OC),** which is a continuous action sequence for a targeted object.

Therefore, according to the definition of the KOAP, the accuracy of a learner's operational portfolio of a Web-based operation experiment tool can thus be automatically assessed, analyzed, and diagnosed. Table 6.1 illustrates examples of the KOAP with descriptions.

Table 6.1: Illustration with the Description of each KOAP

Type	Illustration	Description
Key Action (KA)		[Filling] the [Red Water] in a [cup without scale] into the [Beaker with Scale] is a Key Action (KA).
Action Continuity (AC)		In order to sniff out the fire correctly, [Action 1] must be followed by [Action 2] and it's not allowable to operate other actions between them.
Action Sequence (AS)		AS=(a_1, a_2, a_5, a_8) is a correct operational action sequence to finish the operation experiment, where [Action 2] must be done before [Action 5], but other actions can be operated between Action 2 and Action 5.
Object Continuity (OC)		For the targeted object, Celery, it must be [Cut] only after [Dip into water]. It will be regarded as the incorrect operation if there are other actions between them.

6.3.2 Embedded Assessment Function

In the OPASS, the rule-based inference approach has been applied to infer the accuracy of the assessment experiment according to a learner's assessment portfolio. Therefore, the teacher can define Assessment Rules (AR) in advance to evaluate the accuracy of a learner's answer and to identify learning problems related to subject concepts, cause and effect operations, and skills of scientific inquiry. The assessment rule can be defined by the following definition.

Definitions of the Assesment Rule (AR):

- ***AR***={Ar_1, Ar_2,…, Ar_n}, where:

- **Ar_i=If (*Condition Setting*) Then (*Assessment Function*):** each Ar_i of AR can be represented by the IF-THEN rule format, where:

- ***Condition Setting* ={Cs_1, Cs_2,…, Cs_m} :** each **Cs_i** of the *Condition Setting* can be used to evaluate the accuracy of the learner's answer in terms of the assessment portfolio consisting of planning data and operational data defined in sub-chapter 6.1. If the result of the ***Condition Setting*** is true, the ***Assessment Function*** will be triggered to evaluate the learner's assessment portfolio.

In the OPASS, the Predicate Function has been applied to be the function used in the AR. A predicate function is defined to be any function that returns TRUE or FALSE. Therefore, any value other than FALSE is considered as TRUE. The predicate function always returns a Boolean value. The ***Assessment Function*** used in the AR is defined as follows.

Definitions of the Assessment Function in AR:

- ***WrongStep*(Step$_i$, Problem$_i$):** checks the experiment Step$_i$ of the assessment procedure, which was executed correctly or not during the Web-based scientific inquiry experiment, where:
  - **Step$_i$**: the name of an experiment step in the scientific inquiry assessment experiment.
  - **Problem$_i$**: denotes a checking predicate function, which can check whether a learner made this kind of problem at an executed experiment **Step$_i$**. Therefore, each Problem$_i$ has its corresponding checking predicate function definition, which can be extended and defined by the teacher according to requirements of the assessment, such as:

◆ ***ObjectContinuity_Error*(obj$_k$, *ActionSequence$_m$*, *WrongPattern$_n$*)**: checks the accuracy of the continuity of the object (obj$_k$) defined in the KOAP according to the comparison between the correct Object Continuity (OC) (***ActionSequence$_m$***) and the learner-made action pattern, which will be regarded as *WrongPattern$_n$* if it is not the correct experimental operation.

◆ ***IndependentVariable_Error*(obj$_k$, *IF-Statement$_n$*, *Then-Statement$_n$*)**: checks the accuracy of the independent variable of the object (obj$_k$) according to the hypothesis setting (*IF-Statement$_n$ and Then-Statement$_n$*), defined in Subsection 6.3.4: Assessment Portfolio, that the learner made.

Example 6.1:

If a learner dipped a stalk of celery into water and then used a knife to cut its root during the virtual operation experiment, the accuracy of this experimental operation the learner made can thus be checked by defined Assessment Functions, ***WrongStep**("Action Operation", ObjectContinuity_Error*([celery], [dip in water] [cut root] [put into tank] [waiting], [dip in water] [cut root]). Therefore, learners' operational actions, i.e., [dip in water] [cut root], are not correct because the correct object continuity definition (OC) of Key Operation Action Patterns (KOAP) was defined as [dip in water] [cut root] [put into tank] [waiting]. Moreover, the accuracy of the hypothesis setting can also be checked by the ***WrongStep**("Operational Experiment", IndependentVariable_Error*([celery], [cross section area of celery stem], [the decreasing quantity of the red water]).

Condition Setting Function in AR:

In addition to the assessment function, the condition setting of the AR can also use the predicate function to check the condition of a rule. Therefore, in the HKD, the ***Condition***

Setting={Cs_1, Cs_2,…, Cs_m}, where, for instance, the Cs_i=***NotMatch***(*ObjectContinuity*(targeted object, correct OC definition): evaluates the accuracy between the correct OC definition and the learner's operational actions in terms of the targeted object, or Cs_j=(*TargetObject*(obj) & *IdependentVriable*(X) & *CorrectIdependentVriable*(Y) & (X≠Y)): evaluates the accuracy between the correct independent variable (Y) and the actual one that the learner set (X) in terms of the targeted object (obj) and the condition will be true if the (X≠Y) is true.

Example 6.2:

Assume there are Ar_1=**If** (*NotMatch*(*ObjectContinuity*([celery], { [dip in water], [cut root], [put into tank] [waiting]})) **Then** ***WrongStep***(*"Action Operation", ObjectContinuity_Error*([celery], {[dip in water], [cut root], [put into tank], [waiting]), {[dip in water], [cut root]}), and Ar_2 = **If** (*TargetObject*([celery]) & *IdependentVriable*([length of stem]) & *CorrectIdependentVriable*([amount of leaves]) & ([length of stem]≠[amount of leaves])) **Then** ***WrongStep***(*"Operational Experiment", IndependentVariable_Error*([celery], [cross section area of celery stem], [the decreasing quantity of the red water])). Therefore, the Assessment Function, *WrongStep*(), will be triggered if the *Condition Setting* of the Ar_1 or the Ar_2 is true.

6.3.3 Assessment Portfolio

The assessment portfolio of scientific inquiry consists of planning data and operational data. Before the assessment process, the log of the Web-based experiment system must be transformed into the defined format in the HKD. Logs of planning data, as shown in Table 6.2, are the set of attribute-value pairs. For example, in an experiment of biology transpiration, learners defined a hypothesis: *If the [celery]'s [leaves] are [more], the [decreasing quantity] of the [red water] is [more]*. Then, logs recorded six attributes, including objects, attributes, and their changes in the condition and effect parts of the hypothesis.

Table 6.2: Example Logs of Planning Data

Attribute	**Value**	**Attribute**	**Value**
Hypothesis-IF-Object	Celery	Hypothesis-THEN-Object	Red water
Hypothesis-IF-Attribute	Leaves	Hypothesis-THEN-Attribute	Decreasing quantity
Hypothesis-IF-Value	More	Hypothesis-THEN-Value	More

Logs of operational data, as shown in Table 6.3, were a sequence of operations, which consists of an action name, a used object, an object of target, and a set of environmental attribute-value pairs. For example, the action sequence in Table 6.3 described that a learner [fill] a [beaker with scale] with [red water]. Then, the learner [dip] a [head of celery] into a [tank] and use a [knife] to [cut] the [stem of the celery]. Afterward, this learner [put] the [celery] into the [beaker with scale] and [waited].

Table 6.3: Example Logs of Operational Data

Action	Used Object	Target Object	Environmental Status
Fill	Red water	Beaker with scale	Temperature: *25℃*, Light: *Yes*, Humility: *60%*
Dip	Celery	Tank	Temperature: *25℃*, Light: *Yes*, Humility: *60%*
Cut	Knife	Celery	Temperature: *25℃*, Light: *Yes*, Humility: *60%*
Put	Celery	Beaker with scale	Temperature: *25℃*, Light: *Yes*, Humility: *60%*
Wait			Temperature: *25℃*, Light: *Yes*, Humility: *60%*

6.4 Diagnosis Proccess

By means the teacher-defined assessment knowledge related to the scientific inquiry experiment described in the previous section, the learner's assessment portfolio can thus be automatically evaluated and diagnosed by the Online Assessment Portfolio Diagnosis Process (OAPDP) in phase 2 of the HKD. The details will be described in this chapter.

Figure 6.3 shows the flowchart of the OAPDP, which consists of three modules: (1) Evaluation Process; (2) Diagnosis Process; and (3) Diagnostic Report Generation. In the Evaluation Process, the OAPDP uses the teacher-defined Assessment Rule (AR) to evaluate the accuracy of the learners' scientific inquiry assessment portfolio and then finds the **Wrong Experiment Step** from the assessment result according to the inference results of the Rule Inference Process. Afterwards, in the Diagnosis Process, the OAPDP first diagnoses the mis-concept/skill with the corresponding reason for each wrong experiment step by means of the Diagnosis Rule (DR) based on the relation model of assessment knowledge as seen in Figure 6.1 and Figure 6.2. The OAPDP further analyzes the Remedial Path according to relational definitions of the experiment knowledge, i.e., the prerequisite (*PR*) in the CM and the Dependence (*D*) in the SM of scientific inquiry. Consequently, the Major mis-concept/skill with the corresponding wrong experiment step can be discovered. Finally, the Diagnostic Report Generation module is able to generate the personalized scientific inquiry diagnostic report consisting of descriptions, corresponding reasons, and related remedial suggestions to correct learning problems based on the defined Description Format.

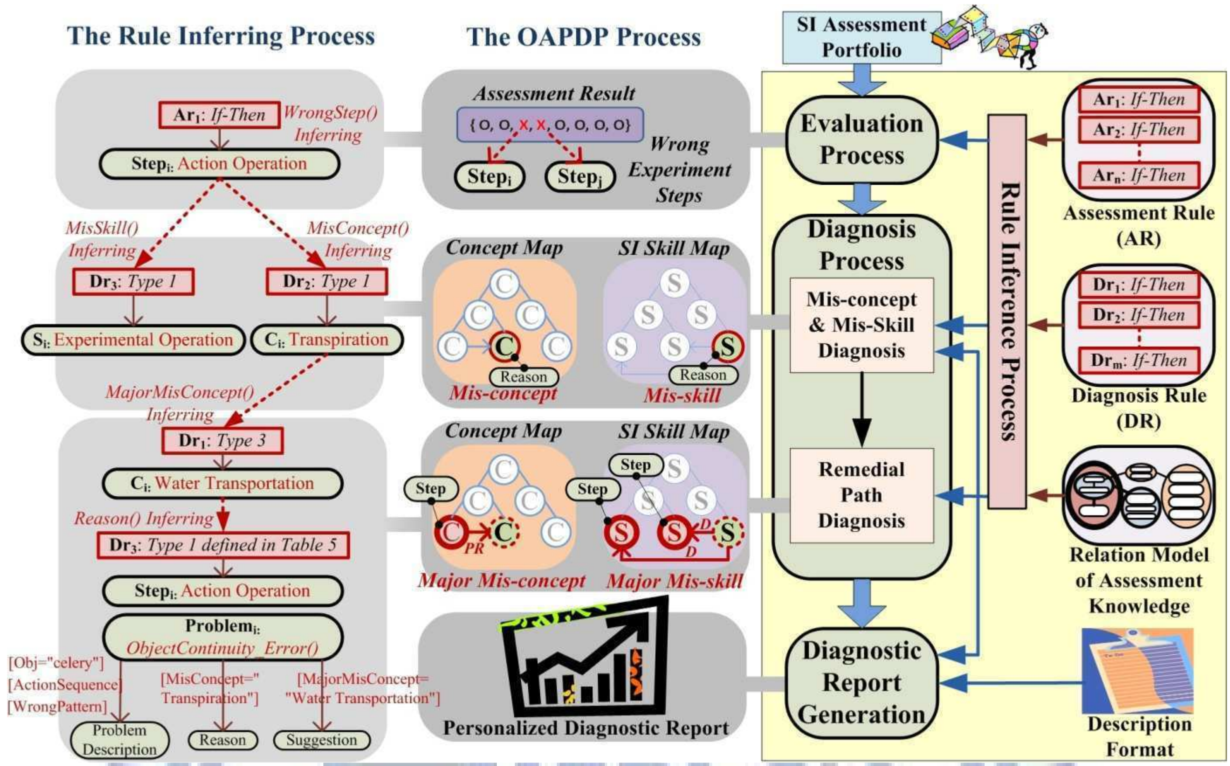


Figure 6.3: Flowchart of the OAPDP

6.4.1 Diagnostic Rules

As mentioned above, the Diagnosis Process module in the OAPDP uses the Diagnosis Rule (DR) based on the relation model of assessment knowledge to diagnose the mis-concept/skill with the corresponding reason for each wrong experiment step. In the OPASS, the DR has thus been proposed and defined as follows.

Definitions of the Diagnosis Rule (DR):

- ***DR***={Dr_1, Dr_2,…, Dr_n}, where:
- **Dr_i=If (*Condition Setting*) Then (*Diagnostic Function*):** each Dr_i of the DR can be represented by the IF-THEN rule format, where three types of DRs are defined as follows:

DRs of the weak concepts, skills, and reasons:

- If (*WrongStep*($S, $P) & *StepConceptRelation*(*WrongStep*($S, $P), $Concept)) Then *MisConcept($Concept)*: diagnoses the weak concept(*MisConcept*()) according to the relationship between the wrong experiment step (*WrongStep*()) and the associated concept by the function *StepConceptRelation*(). The \$S and \$P denote the Step_i and the Problem_i of Assessment Function, *WrongStep*(), in AR.

- If (*WrongStep*(\$S, \$P) & *StepSkillRelation* (*WrongStep (\$S, \$P), \$Skill*)) Then *MisSkill(\$Skill)*: diagnoses the weak skill according to the relationship between the wrong experiment step and associated skill of scientific inquiry by the function *StepSkillRelation*().
- If (*WrongStep*(\$S, \$P) & *StepReasonRelation*(*WrongStep(\$S, \$P), \$Type,* \$Desc)) Then *Reason(\$Type, \$Desc)*: diagnoses the corresponding reason of occurred weak conceptor weak skill according to the relationship between the wrong experiment step and associated reason, where Type is "Concept" or "Skill," each of which has a corresponding description (\$Desc) to explain the reason for a problem that a learner made for the wrong experiment step.
- DRs of the Major Wrong Step of Assessment Experiment:
- If (*MajorMisSkill*(\$Skill) & *WrongStep*(\$S,\$P*) & StepSkillRelation*(*WrongStep*(\$S, \$P), \$Skill)) Then *MajorWrongStep*(\$S, \$P): diagnoses the major wrong experiment steps of a learner according to the relationship between the wrong experiment and the major weak skill.
- DRs of the Remedial Concept and Skill of weak concept and weak skill:
- If (*MajorMisConcept*(\$Cx) & *Prerequisite*(\$Cy, \$Cx)) Then *PRConcept*(\$Cy): diagnoses the remedial concept of the learner's mis-concpet according to the prerequisite concept relationship (*Prerequisite*()) of the major mis-concept.
- IF(*MajorMisSkill*(\$Sx) & *Prerequisite*(\$Sy, \$Sx)) Then *PRSkill*(\$Sy) : diagnoses the remedial skill of the learner's weak skill according to the prerequisite skill relationship (*Prerequisite*()) of the major weak skill.

Table 6.4 lists examples of the DR Definition and Table 6.5 also presents examples of the Assessment Function Definition, *WrongStep*(\$S, \$P), associated with the Problem Description, the Reason, and the Suggestion Description. The learning problems related to the concepts, cause and effect operations, and skills of scientific inquiry can thus be analyzed and diagnosed by means of the proposed DR.

Table 6.4: Example of Three Types in the DR Definition

Type		IF *(Condition Setting)*	THEN
Symbol Definitions		$S1=*"Operational Experiment"* $S2=*" Action Operation"* $P1=*IndependentVariable_Error*([celery], [cross section area of celery stem], [the decreasing quantity of the red water])) $P2= *ObjectContinuity_Error*([celery], {[dip in water], [cut root], [put into tank], [waiting]), {[dip in water], [cut root]}	
Type 1	Dr_1	*WrongStep*($S1, $P1) & *StepConceptRelation*(*WrongStep*($S1, $P1)), "*Transpiration*")	*MisConcept*("*Transpiration*")
	Dr_2	*WrongStep*($S2, $P2) & *StepConceptRelation*(*WrongStep*($S2, $P2)), "*Transpiration*")	
	Dr_3	*WrongStep*($S2, $P2) & *StepSkillRelation* (*WrongStep*($S2, $P2)), "*Transpiration*")	*MisSkill*("*Experimental Operation* ")
Type 2	Dr_1	*MajorMisSkill*("*Experiment Planning*") & *WrongStep*($S1, $P1) & *StepSkillRelation*(*WrongStep(*$S1, $P1), "*Experiment Planning*")	*MajorWrongStep*($S1,$P1)
	Dr_2	*MajorMisSkill*("*Experimental Operation*") & *WrongStep*($S2, $P2) & *StepSkillRelation*(*WrongStep*($S2, $P2), "*Experimental Operation*")	*MajorWrongStep*($S2, $P2)
Type 3	Dr_1	*MajorMisConcept*("*Transpiration*")& *Prerequisite*("*Water Transportation*", "*Transpiration*")	*PRConcept*("*Water Transportation*")
	Dr_2	*MajorMisSkill*("*Setting Variable*") & *Prerequisite*("*Making Hypothesis*", "*Setting Variable*")	*PRSkill*("*Making Hypothesis*")

Table 6.5: Example of *WrongStep*($S, $P) Definition Associated with Problem Description, Reason, and Suggestion Description in the OPASS

DR	Step ($S)	Problem ($P)	Problem Description (A), Reason (B), Suggestion Description (C)	
Dr$_1$	Making Hypothesis	*Hypothesi_Error*(scene, IF-Statement, Then-Statement)	A	Because the solution that you made in the [scene] is that "IF [IF-Statement] THEN [Then-Statement]", it can not solve the problem of the experiment.
			C	Please carefully read the "Problem Description" of [scene] again and try to use another approcah to solve it.
Dr$_2$	Operational Experiment	*VariableOperation_ Error*(Variable)	A	The [Variable] you operate is not the same variable you set in the Setting Variable Step of the experiment.
			B	Reason("Skill","the variable that you set in the Setting Variable Step of the experiment can not be operated in this experiment")
			C	You must operate the same variale in the Setting Variable Step and the Operational Experiment Step both.
Dr$_3$	Action Operation	*ObjectContinuity_ Error* (Obj, ActionSequence, WrongPattern))	A	Because the [Obj] must be operated by [ActionSequence], we guess that your operation order [WrongPattern] is wrong.
			B	Reason("Concept", "you may not thoroughly understand the [MisConcept] ")
			C	We suggest that you should learn the [MajorMisConcept] and [MisConcept] in advance。

Example 6.3:

The left-hand side of Figure 6.3 illustrates the rule inferring process during the OAPDP process by employing the rule-based inference approach. To follow the descriptions in previous examples, if the Ar$_1$ in AR come to be true, a Wrong Experiment Step, "Action Operation," can be found from the assessment portfolio of scientific inquiry in the Evaluation Process. Therefore, In the Diagnosis Process, after the weak concept and week skill diagnosis, the week concept, "Transpiration," and the weak skill, “Experimental Operation," at this "Action Operation" step can be inferred by using the Dr2 of Type 1 and the Dr3 of Type 1 in DR in Table 4, respectively. Afterwards, in the Remedial Path Diagnosis, the major mis-concept, "Water Transportation," can be found through the Dr1 of Type 3, and according to the inferred mis-concpet and the definition of the concept map in Figure 3. Finally, by using the aforementioned results, the Dr3 in Table 6.5 was triggered to reason and diagnose the learning problems with Problem Description, Reason, and Suggestion Description for this wrong experiment step, "Action Operation,". Consequently, the personalized diagnostic results can be offered to the learner as follows: You had the wrong experiment step at [Action Operation Step], (A) because the [Obj="celery"] must be operated by [ActionSequence="[celery], {[dip in water], [cut root], [put into tank], [waiting]"], we guess that your operation order [WrongPattern="[dip in water], [cut root]"] is wrong. (B) The Reason is taht "you may not thoroughly understand the [MisConcept="Transpiration"] "). (C) We suggest that you should learn the [MajorMisConcept="Water Transportation"] and ["MisConcept="Transpiration"] in advance. Consequently, the various learning problems, concerning conceptual knowledge, cause and effect operations, and skills of scientific inquiry, with corresponding reasons and remedial suggestions can be automatically analyzed and diagnosed by the Diagnosis Process in the OAPDP. These diagnostic results will be further organized and syntheized into a readable and understandable resport in the Diagnostic Report Generation in the OAPDP.

6.4.2 Diagnostic Report Generation

After the Evaluation and Diagnosis process modules have been processed, the learners' learning problems in relation to the concepts, cause and effect operations, and skills of the scientific inquiry experiment can be diagnosed, and corresponding reasons and descriptions can also be acquired. The personalized diagnostic report can thus be generated by running the Diagnostic Report Generation in the OAPDP. The proposed **Diagnostic Report Generation Algorithm (DRGalgo)** is described in **DRGalgo**, and Figure 6.4 shows an example of the personalized diagnostic report generated by the DRGalgo.

Algorithm 6.1: Diagnostic Report Generation Algorithm (DRGalgo)

Symbol Definition:
***$WrongStep_i$*:** the detected wrong experiment step of SI experiment for the learner.
***MisConcept*:** the detected weak conceptof the learner.
***MisSkill*:** the detected weak skill of the learner.
***MajorWrongStep*:** the detected major wrong step of SI experiment for the learner.
***MajorMisConcept*:** the detected major weak conceptof the learner.
***MajorMisSkill*:** the detected major weak skill of the learner.
***PRConcept*:** the prerequisite concept of a concept.
$: output the value of variable

Input: All detected wrong experiment steps of SI assessment experiment
Output: Personalized Diagnostic Report

Step 1: Generate the detailed description for each Wrong Step (*$WrongStep_i$*)of Assessment Experiment,
1.1: output the statement: "[Problem]: you made wrong action at [$*$WrongStep_i$*] Step."
1.2: output the statement: "[Corresponding Skill]: [$*MisSkill*]."
1.3: output the statement: "[Phenomenon]: [$(*the Problem Description of $WrongStep_i$*)]
1.4: If Reason.Type = "Concept"
Then output the statement: "[Possible Reason]: you may not thoroughly understand the [$*MisConcept*]."
Else If Reason.Type = "Skill"
Then output the statement: "[Possible Reason]: because [$(*the Reason Description of $WrongStep_i$*)] for the [$*MisSkill*]"
1.5: output the statement: "[Suggestion]: [$(*the Suggestion Description of $WrongStep_i$*)]
Step 2: Generate the overall diagnostic description for learner's assessment result
2.1: If [conclusion is wrong]
Then
Output the statement: "[Problem]: your conclusion is wrong. The possible reason may be the [$(*the Problem Description of the MajorWrongStep*)]."
Output the statement: "[Skill Suggestion]: [$(*the Suggestion Description of MajorWrongStep*)]."
Output the statement: "[Concept Suggestion]: for the concept of subject in this experiment, suggest that you need to thoroughly lean and understand the concept of [$*MajorMisConcept*].
Output the statement: "[Prerequisite Concept Suggestion]: other than the concept [$*MajorMisConcept*], suggest that you can also thoroughly learn and understand its prerequisite concept [$*PRConcept*].
Step 3: Output the Personalized Diagnostic Report

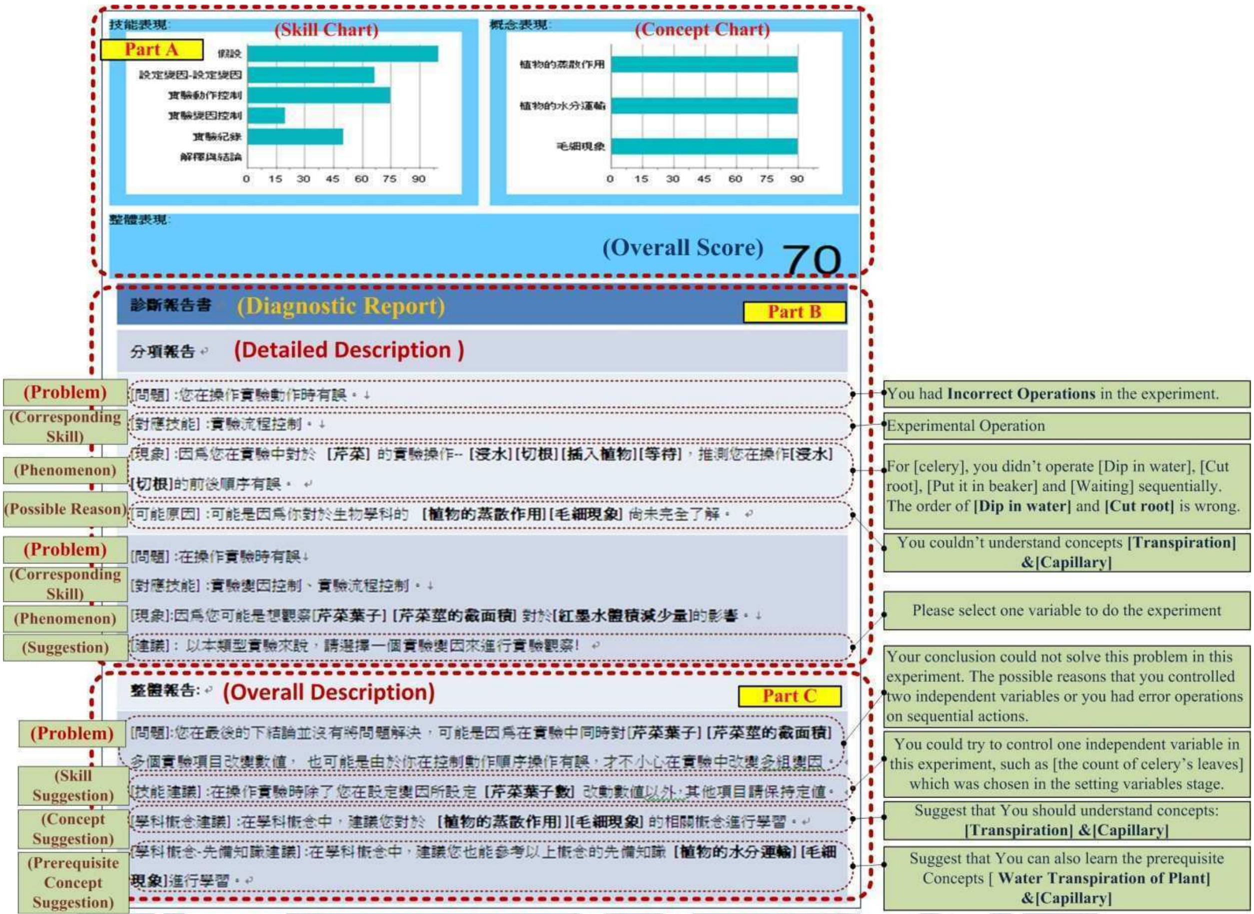


Figure 6.4: Example of the Personalized Diagnostic Report Generated by DRGalgo in OPASS

6.5 Experimental Results

6.5.1 Experimental Plan and Execution

In order to evaluate the performance of the HKD, a prototypical system, named Online Portfolio Assessment and Diagnosis Scheme (OPASS) [83], was developed and several experiments were conducted. Two classes, from different schools in Taiwan, participated in the assessment experiments. Thirty first-grade learners of high school, in the urban district, and ten third-grade learners of junior high school, in the remote district, participated in the assessment experiments of scientific inquiry in Biology and Physics, respectively. First, teachers explained the purpose of the experiment and taught learners how to use the Web-based scientific inquiry experiment system (OPASS). Learners could practice and familiarize themselves with the system by participating in the testing experiment (Figure 6.5a). Following the practice test, the learners took the formal assessment experiments (Figure 6.5b) to understand their learning problems by means of personalized diagnostic reports (Figure 6.5c). Finally, a questionnaire of a five-level Likert Scale, as seen in Table 6.6, was designed and provided to learners to evaluate their degrees of satisfaction concerning the OPASS system.

Table 6.6: Questionnaire of Learners' Degrees of Satisfaction of the OPASS System (Five-Level Likert Scale from 1 (Strongly Disagree) to 5 (Strongly Agree))

Q1: It would be helpful to provide personalized analysis and learning suggestions concerning the operation and examination after the assessment experiment.
Q2: In **Part A** of the diagnosis report, the bar charts of skills, concepts, and overall scores can assist you in understanding your assessment outcome.
Q3: In **Part B** of the diagnosis report, the descriptions consisting of the wrong plans, wrong operations, reasons, and possible remedial suggestions can assist you in understanding the problems during the experiment.
Q4: In **Part C** of the diagnosis reports, the descriptions concerning the overall diagnosis and suggestions can improve your learning.
Q5: This diagnosis report is useful and can improve your learning efficacy.

Figure 6.5: (a) Learners Practicing the OPASS, (b) Taking the Examination, and (c) Reading the Diagnostic Report Regarding the Scientific Inquiry Experiment in the Physics Domain

6.5.2 Analysis of Learners' Scores with Prior Knowledge Measures

Correlations of OPASS Scores with Prior Knowledge Measures

Examining the correlations of the OPASS scores with each measure of prior knowledge can help clarify meaning. For example, learners with more prior knowledge tended to perform better on each score of the OPASS than learners with lower levels of prior knowledge. The prior knowledge measures were intended to give an indication of the degree of learner familiarity with the science and related concepts being assessed in the scientific inquiry experiments of the OPASS system [9]. In this paper, the prior knowledge measures consist of two kinds of knowledge: (1) Science Knowledge; and (2) Scientific Inquiry. The prior science knowledge measure was designed to be related to the Physics and Biology domain. Therefore, the grade of a learner of Physics and Biology at school was adopted as the prior science knowledge measure.

The prior scientific inquiry knowledge measure was intended to concern skills of scientific inquiry. In order to assess prior scientific inquiry knowledge of participant learners, a comprehensive Test of Integrated Science Process Skill (TIPS) was developed by [22]. This test included integrated science process skills (e.g., stating hypotheses, controlling variables, designing experiments, operational definition, graphing and interpreting data) and was adopted as a reference to design a Chinese version. The TIPS had a high reliability (0.89) and was non-curriculum-specific for the middle and secondary schools. Afterwards, Burn, Okey, and Wise. [10] developed the TIPS II based on the original TIPS.

By means of the data collected from the experiments of the OPASS system, Table 6.7 lists the summary statistics of the Prior Science Knowledge and the OPASS Measures for the 30 first-grade high school learners (Grade 10) in the Physics domain (effective sample size (N) = 24). Table 6.8 presents the correlations of the "Total Score" of the OPASS, consisting of "Scientific Inquiry" and "Science Knowledge", with the two prior knowledge measures, "Science Knowledge" and "Scientific Inquiry knowledge".

Table 6.7: Summary Statistics for Prior Knowledge and OPASS Measures – Grade 10, Physics domain

Measures / Statistic	Prior Science Knowledge		OPASS		
	Science Knowledge: Grade in Physics	Scientific Inquiry: Total Score of TIPS	Total Score	Scientific Inquiry	Science Knowledge
Number of Learners (N)	24	24	24	24	24
Mean Score	71.88	72.64	75.83	79.17	72.50
Standard Deviation (SD)	9.205	7.982	9.289	8.456	12.324

Table 6.8: Correlations of OPASS Scores with Prior Knowledge Measures in TIPS – Grade 10, Physics Domain

OPASS Score	Prior Science Knowledge: Grade in Physics	Prior Scientific Inquiry Knowledge: Total Score of TIPS
Total	-.263	.431*
Scientific Inquiry	-.156	.492*
Science Knowledge	-.290	.313

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

According to the correlations in Table 6.8, the “Total” score of OPASS did not correlate with the two prior knowledge measures: “Science Knowledge: Grade in Physics” and “Prior Scientific Inquiry Knowledge: Total Score of TIPS.” In addition, the “Prior Science Knowledge” did not correlate with the “Prior Scientific Inquiry Knowledge.” This indicates that the mastery levels of learners’ grades in Physics may not influence the performance of OPASS and TIPS.

Besides, the “Total” score of TIPS has the significant positive correlations with the “Total” score (0.431, $p<.05$) and “Scientific Inquiry” (0.492, $p<.05$) of OPASS, respectively. This means that learners with more prior scientific inquiry knowledge tend to perform better on “Total” and “Scientific Inquiry” scores of the OPASS. Furthermore, the “Scientific Inquiry” of OPASS has a significant positive correlation (0.584, $p<.01$) with the “Science Knowledge” of OPASS. The reason for this outcome is that the OPASS system integrated the scientific inquiry skills and science knowledge together with each step and action of the Web-based assessment procedure.

According to the results of Table 6.8, the "Total" score of the OPASS has a significant correlation with the TIPS score. In this paper, the "Scientific Inquiry" score of OPASS consists of five scales: (1) Making Hypothesis; (2) Setting Variables; (3) Experimenting; (4) Graphing; and (5) Concluding. For estimating the correlations, the TIPS scales were mapped to these five OPASS scales. Therefore, the correlations of each sub-score of OPASS with TIPS are shown in Table 9 to investigate the reliability and validity of the OPASS system.

Table 6.9: Correlations of OPASS Scores with Prior Knowledge Measures in TIPS – Grade 10, Physics Domain

TIPS Score / OPASS Score	Making Hypothesis	Setting Variables	Experimenting	Graphing	Concluding
Total	.031	.506*	.271	.235	.203
Scientific Inquiry	.059	.352	.237	.149	.210
Science Knowledge	.005	.509*	.240	.245	.158
(1) Making Hypothesis	.a	.a	.a	.a	.a
(2) Setting Variables	.025	.593**	.147	-.062	.166
(3) Experimenting	-.145	.254	.120	-.073	-.054
(4) Graphing	.199	.147	.303	.646**	.351
(5) Concluding	-.038	-.151	-.074	-.320	-.094

a. Cannot be computed because at least one of the variables is constant.

As Table 6.9 shows, the correlation values of "Making Hypothesis" (OPASS) with TIPS cannot be computed because all learners correctly performed this step in OPASS. The "Concluding" (OPASS) also did not correlate with the one of TIPS because 19 out of 24 learners were correct. The reason for this is that learners learned concepts and skills related to "Making Hypothesis" and "Concluding" in the practice section, and such learning effects subsequently became prior knowledge when the learners took the online assessment of scientific inquiry in the examination section, as depicted in Figure 6.5.

The "Experimenting" portion (OPASS) has no significant positive correlation with the one of TIPS. That is because learners were required to interact and operate the Web-based operation experiments at the “Experimenting” step in the OPASS system, which can be regarded as a "hands-on" assessment. The operational data of learners, as shown in Table 6.3, were recorded and collected in the assessment portfolio and assessed according to the teacher-defined assessment knowledge definition, e.g., Key Operation Action Pattern (KOAP). On the contrary, the TIPS is a paper-and pencil test and is a suitable approach to measure learners' knowledge of scientific concepts and inquiry (e.g., Substantive Knowledge, but it is not easy to assess and evaluate learning problems and performance of higher-order capabilities related to scientific inquiry.

Furthermore, the “Setting Variables” and “Graphing” in the OPASS system have significant positive correlations (0.593 and 0.646, $p < 0.01$) with the ones of TIPS, respectively. Those correlations describe that learners with more prior knowledge in terms of “Setting Variables” and “Graphing” in TIPS tend to perform better on corresponding scales in the OPASS system than learners with lower levels. Consequently, the significant correlations between the OPASS and the TIPS can show that the OPASS system is able to perform a reliable and valid assessment of scientific inquiry.

In addition to the evaluation for grade 9 learners in the Biology domain at the urban district, the prototypical OPASS system was evaluated by 10 grade 9 learners who reside in the remote district, as listed in Table 6.10 and Table 6.11, respectively. The results show that the performance of the OPASS has no significant correlations with the “Prior Knowledge” of learners in terms of “Average of Subjects” and “Grade in Biology,” which is the same as the experiment results in Physics.

Table 6.10: Summary Statistics for Prior Knowledge and OPASS Measures – Grade 9, Biology Domain

Measures / Statistic	Prior Knowledge		OPASS		
	Knowledge: Average of Subjects	Science Knowledge: Grade in Biology	Total Score	Scientific Inquiry	Science Knowledge
Number of Learners (N)	10	10	10	10	10
Mean Score	75.27	78.83	56.83	62.00	51.67
Standard Deviation (SD)	9.536	9.425	18.316	16.633	23.107

Table 6.11: Correlations of OPASS Scores with Prior Knowledge Measures – Grade 9, Biology Domain

OPASS Score	Prior Knowledge: Average of Subjects	Prior Science Knowledge: Grade in Biology
Total	.065	.132
Scientific Inquiry	-.070	.056
Science Knowledge	.154	.168

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

6.5.3 Assessment Accuracy of the OPASS System through Domain Experts

In addition to the evaluation by the correlations between the OPASS system and a comprehensive TIPS test with high reliability and validity, the evaluations of domain experts are also important for evaluating the accuracy of diagnostic reports [86]. Therefore, an evaluation tool was developed to allow the domain expert to review and evaluate the accuracies of the diagnostic results of each learner by checking the assessment portfolios. Three teachers as domain experts were invited to evaluate all learners' experimental logs and score all statements in the diagnostic reports generated by the OPASS system. A statement's score was from 0 to 1. Figure 6.6 shows the statistical results in terms of different parts of the diagnostic report for three tests shown in Figure 6.4. According to evaluation results, the accuracies of the diagnostic reports are very high and meet the professional opinions of the teachers. In addition, the teachers also agreed that automatic, generated diagnostic reports can significantly assist teachers in understanding the status of learners' inquiry abilities. This personalized diagnosis task is difficult for teachers to complete manually.

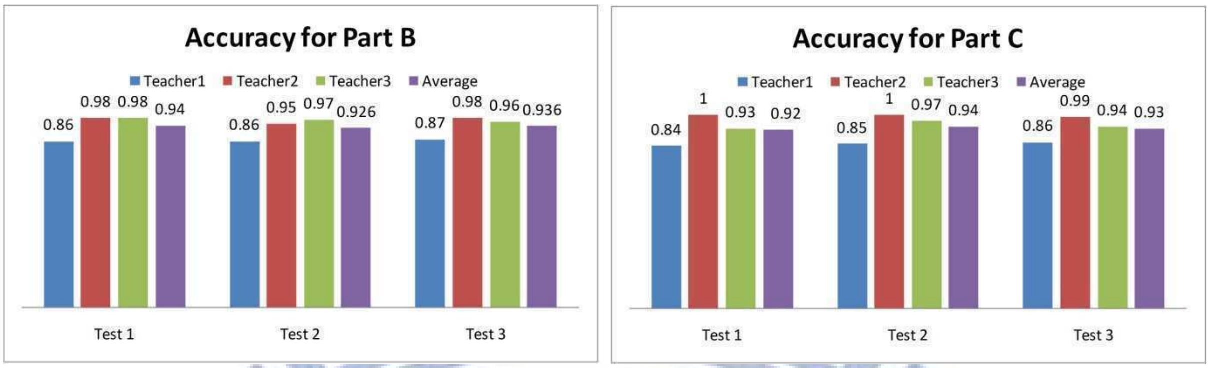


Figure 6.6: Statistical Results of Teachers' Evaluations for Diagnostic Report Accuracies

6.6 Analysis of Learners' Feedback

Figure 6.7 shows the statistical results of the questionnaire (Cronbach's Alpha = 0.825) concerning learners' satisfaction in terms of two classes (N=10 in Class 1 for Biology and N=24 in Class 1 for Physics), as shown in Table 6.6. The satisfaction degree is from 3.86 to 4.2 and the average is 4.17. This shows that most of learners agreed that the diagnostic mechanism and the diagnostic report generated by the OPASS system are useful and can be expected to improve learning efficacy and assist in understanding the learning and operational problems in Web-based scientific inquiry experiments.

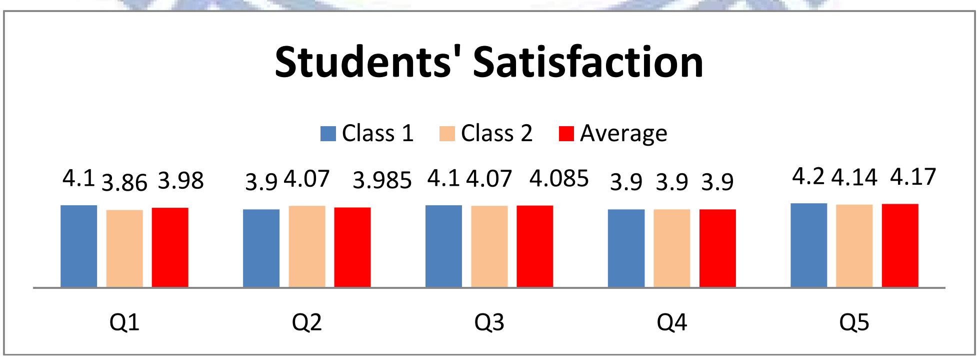


Figure 6.7: Statistical Results of the Questionnaire Concerning the Learners' Satisfaction

Chapter 7 Conclusion

This dissertation aims to propose an automatic adaptive scaffolding scheme to assist learners in science learning in a hypermedia-based learning environment. Because the various learners need personalized learning supports to fulfill their learning needs, the adaptive scaffoldings have to guide learners learning in the non-linear learning process. However, the heterogeneous learning paths and learning portfolios in the non-linear learning process cause the Learning Process Representation Subproblem, the Personalized Content Adaptation Subproblem, and the Process Skill Diagnosis Subproblem. In the Learning Process Representation Problem, a learning process model is needed for teachers to intuitively express the non-linear learning process. To cope with this subproblem, this dissertation proposes a Generalized Finite State Machine, where the input of traditional finite state machine is generalized to a compound input to represent learners' complex learning status. Furthermore, in order to express teachers' learning path-selection knowledge, the disjunction normal form rules are embedded in the transition function to deal with the inputted learning status. In the Personalized Content Adaptation Subproblem, learning content storing in the single granularity usually causes the efficiency issue when providing adapted learning content for a new request. Thus, a Multi-Granularity Content model is used to manage learning content. For a new request, the content can be adapted from coarse-grained to fine-grained to provide efficient and effective content adaptation. In the Process Skill Diagnosis Subproblem, the low-level heterogeneous learning events cannot be connected to the high-level diagnosis knowledge. For this subproblem, an Ability-Centered Knowledge level is proposed, where the background knowledge is represented as knowledge ontology and all learning events can be evaluated to generate predicates of learning status, which represent the ability-related testing performances or learning behaviors. By using the Ability-Centered Knowledge level, the diagnosis knowledge can be applied to assess the heterogeneous learning portfolios to provide learning diagnosis. The three knowledge models can communicate with each other and can provide the integrated learning support for the four phases of learners' self-regulated learning.

Besides the evaluation of satisfaction degrees and scores, the learners' behaviors during the experiments changed. In the experiments of GFSM, we found that the learners in low-grade group tended to plan and implement their learning process more actively, and the learners in high-grade group tended to refer to the suggestions to plan their learning processes. The reason might be that the better understanding of the course makes the low-grade-group learners have more ability to plan learning by themselves, and the high-grade-group learners can reflect on their planning strategies by referring the suggestions. Moreover, in the experiment of HKD, we found learners spent more time trying to correct actions in the virtual experiments by refering to the diagnostic reports. The reason might be that the diagnostic reports can help learners reflect on their learning weakness, which is a clearly learning goal and can motivate learners to remedy it. However, the SRL behavior changes caused by the proposed Novel Adaptive Scaffolding Scheme have not been evaluated precisely and severely. In the future research, more evidences, such as the trends of learning time and attempt times, will be found from learners' learning logs. Moreover, more teaching strategies of constructing and fading scaffoldings will be used to help learners gradually learn to self-regulate their own learning process without assistance and then improve learners' SRL abilities.

In the near future, we aim to help learners regulate not only cognition, but also motivation, because the learning motivation is easy to decrease in the traditional HLE. Thus, we will try to diagnose learners' motivation by analyzing their learning time, behaviors, and context. Based on the diagnosis, the system can provide more suggestions, challenges, and interaction with peers to enhance learners' motivation. Besides, the proposed scaffoldings of planning focus on helping learners who already have learning goals. However, some learners even cannot clearly know their learning directions and goals. Thus, in the near future, we also aim to assist learners in determining learning goals based on their prior knowledge and styles.

Appendix 1. Object-Oriented Learning Activity System

Concept is an established framework of understanding an objects, events, or processes [55]. The theory of Meaningful Learning, proposed by Ausubel [4], describes that in science education the new knowledge must be constructed based on the learners' prerequisite knowledge, named superordinate concept. Gagne [26] also suggested that prior knowledge is the necessary internal condition of learning. Thus, how to suggest meaningful learning process according to learners' ability of concepts is an important and challenging issue to improve learning efficacy.

We have invited in-service teachers to design a scientific learning activity, named "*The evaporation, condensation and boil of water*" based upon the concept of Scaffolding Instruction [76]. Scaffolding Instruction originates from the concept of "*zone of proximal development (ZPD)*", proposed by [90], which means the distance between what learners can do by themselves and what they can be helped to achieve. The teaching strategy of Scaffolding Instruction provides individualized support, named Scaffolding, based on the learner's ZPD [13]. Thus, it is important to clearly evaluate the learners' prior knowledge to provide scaffolding in learners' ZPD. Besides, according to [70], in the scientific learning about water cycle, some misconceptions are generated easily to confuse learners. These misconceptions can make learning more difficult, so in the adaptive learning activity, we aim to find the misconceptions and provide appropriate remedial instructions. The online courses were provided to 62 learners of 5th graders in an elementary school in Taiwan.

Before designing the learning activity, the scope of this learning activity was clearly defined in Figure x1.1. Based on the theory of [27], we organized the related concepts of water cycle in a concept hierarchy, shown in *Figure x1.2*, and collected the data of related misconceptions to construct a misconception hierarchy, shown in Figure x1.3. Accordingly, the knowledge evaluation test items were designed to evaluate the learners' prior knowledge, and the regular learning contents were constructed to teach all related concepts. In order to help learners find and correct misconceptions, the diagnostic test items and the corresponding contents of remedial instruction were constructed. All the learning sequences were designed as flowcharts and further integrated learning resources to construct an online learning activity in OOLA system. This learning activity can be performed after a regular lecture of water cycle to improve the learners' learning efficacy.

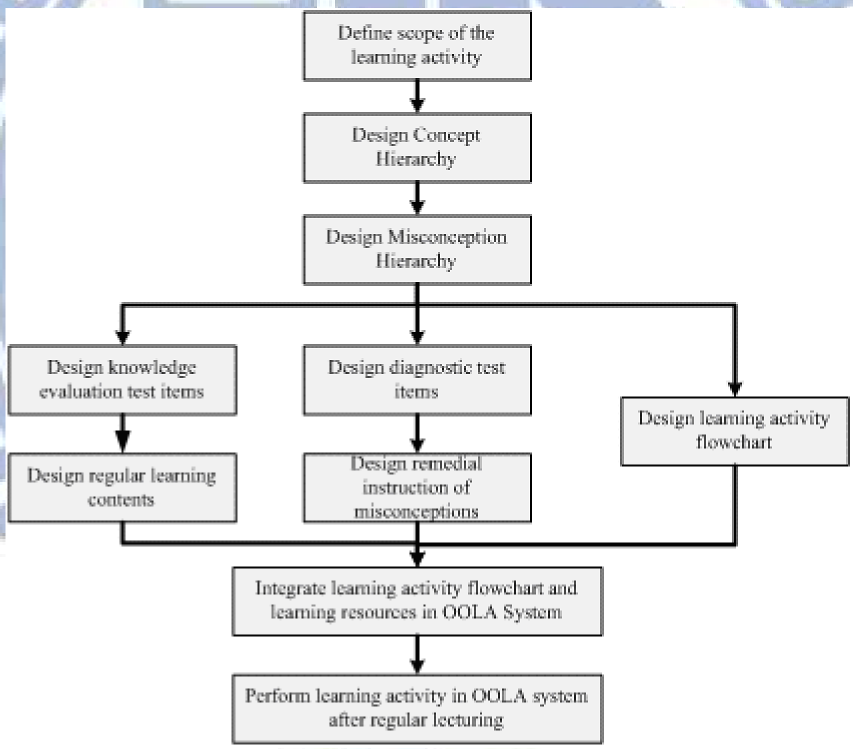


Figure x1.1: Flowchart of designing a learning activity in OOLA system

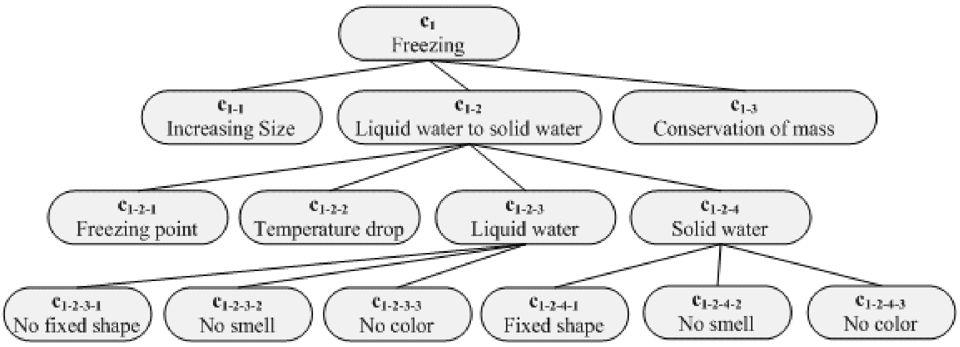


Figure x1.2: A partial concept hierarchy of freezing in water cycle

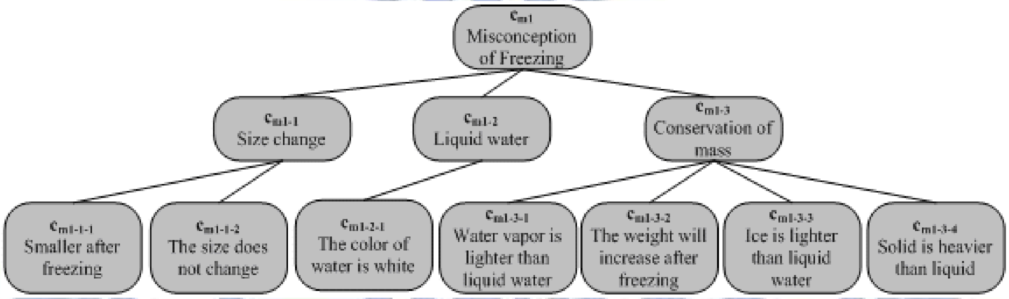


Figure x1.3: The partial misconception hierarchy of freezing in water cycle

In the strategy of the learning activity, shown in Figure x1.4, a course introduction is given as an advance organizer [4], and then a pre test is given to evaluate the prior knowledge of the learner. If the learner has already understood the topic of this learning activity, an activity is provided to enhance the impression. Otherwise, learning contents are provided based on the learner’s prior knowledge. After the concept learning, a post test is given to evaluate the learner’s learning outcomes, and if any concept still can not be handled, the diagnostic test is used to find the misconceptions, which will be remedied by the remedial instructions.

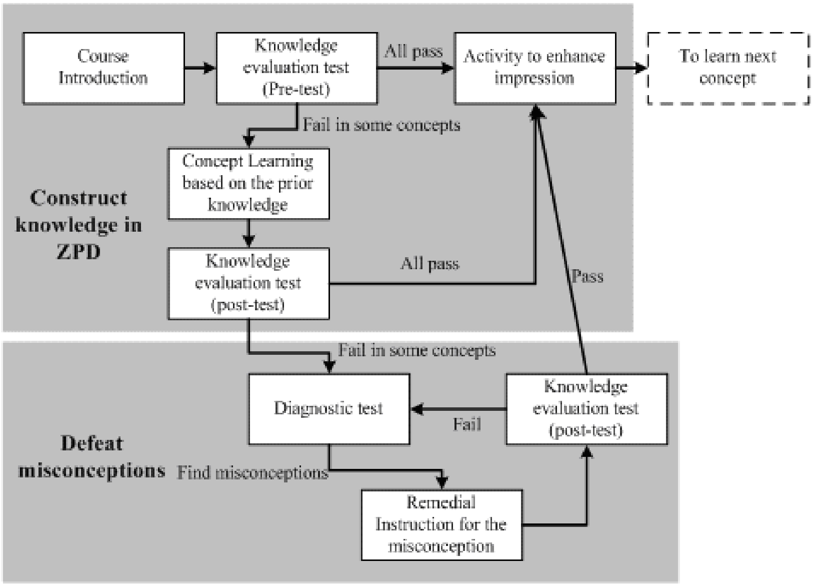


Figure x1.4: The teaching strategy of the scaffolding instruction with misconception diagnosis

Accordingly, as shown in Figure x1.5, the flowcharts of knowledge evaluation test and concept learning in the learning activity were designed. In knowledge evaluation test, the exam about the most general concept c_1, named "*Freezing*", is given to evaluate the overall knowledge of freezing. If c_1 is understood by learners, the learning services of search engine and file-upload service are provided for learners to find related data and upload the reports to teachers. Otherwise, if c_1 can not be totally understood, the evaluation test will drill down to evaluate the prerequisite concepts c_{1-1}, c_{1-2}, and c_{1-3} in the lower level of concept hierarchy and the rest may be deduced by analogy until the concepts of weak understanding in the lowest level are evaluated. Then, the learning contents will be provided to construct knowledge from the lowest level concepts, evaluated in knowledge evaluation test, to the top level concept. In each learning unit object, the learning contents can be hidden if the learner has already had the knowledge. For example, in the matrix of second level contents, $item_1$ will be displayed only if the score of concept c_{1-1} is lower than 0.6, and the $item_4$ will be shown only if the average score of c_{1-1}, c_{1-2}, and c_{1-3} is very low.

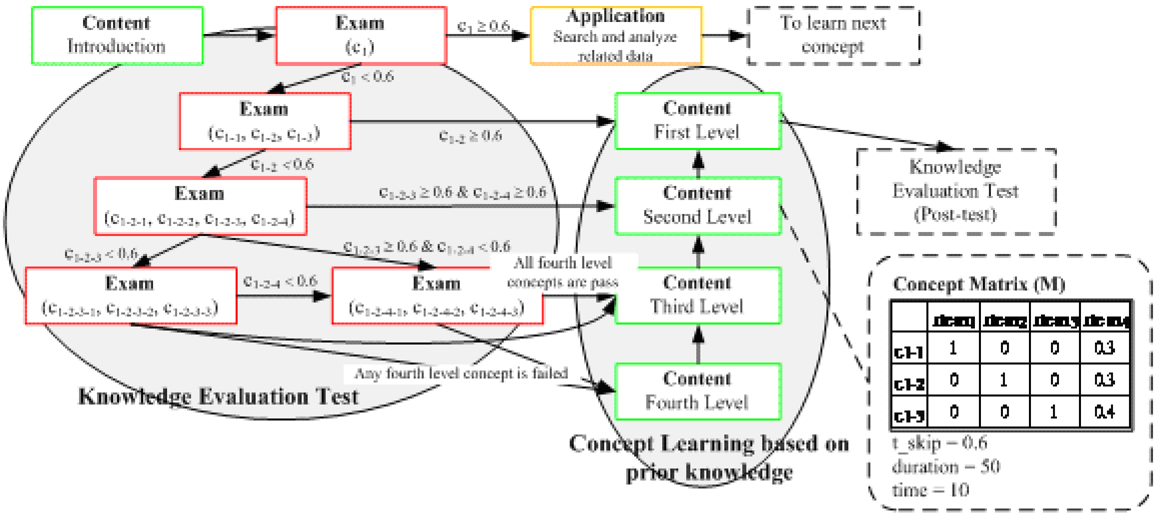


Figure x1.5: A part of flowchart of learning activity “The evaporation, condensation and boil of water”

As shown in Figure x1.6, after concept learning, a post test is given to evaluate the learning performance of all concepts. If any score of concept is still lower than 0.6, a corresponding diagnostic test will be provided to find out the misconceptions, which might cause the low learning performance. Then, the misconceptions can be remedied in the remedial instruction, and the next concept will be diagnosed subsequently.

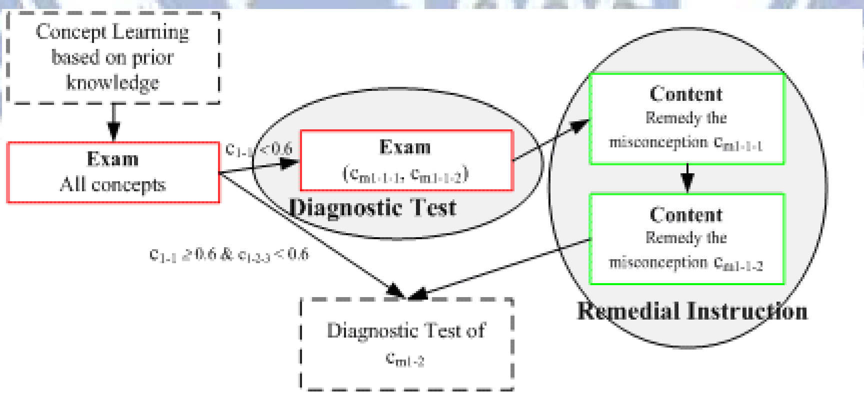


Figure x1.6: A part of flowchart of misconceptions diagnosis and remedial instructions

This application shows how to evaluate a learner’s prior knowledge based on concept hierarchy by the mechanism of adaptive navigation support in OOLA system. In the concept learning, the adaptive presentation mechanism is performed based on the concept matrix to select the appropriate learning contents according to learner's prior knowledge. Moreover, with misconception hierarchy, the learning activity can perform the corresponding diagnosis and remedial instruction for each misconception. Figure x1.7 is the screenshot of authoring tool of OOLA system,

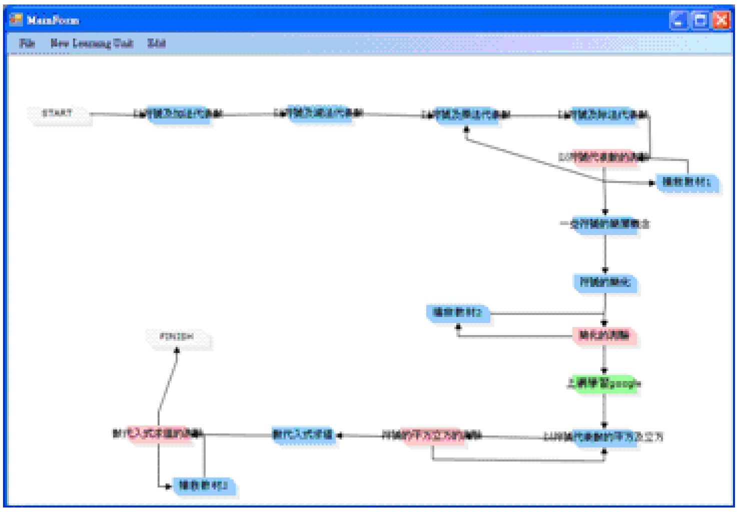


Figure x1.7: Screenshot of the authoring tool of OOLA system

Appendix 2. Personalized Learning Content Adaptation Mechanism

The prototypical PLCAM system was developed on an Apache Server, PHP, Perl and C Language, and a SCORM-compliant LOR. Implementation details and experimental results are described in this section.

The mobile learning scenario for the prototypical PLCAM system deploys a SCORM-compliant Learning Object Repository (LOR) that allows teachers to upload teaching materials. Learners, in turn, can search and download the desired learning content onto their mobile devices. Learners can log in to the system through their mobile devices and manually configure their own Leaner Preference (LP) with Weight Vector (WV). They may then select the learning content to download, and proper personalized learning content will be adapted and delivered by the PLCAM according to the learners' Hardware Profile (HP) and LP, and the status of the wireless networks. As the number of Learner Requests (Σ) increases, the Learning Content Adaptation Management Scheme (LCAMS) will automatically rebuild the Content Adaptation Decision Tree (CADT) and manage the adapted version of the Media Object (MO) in the LOR.

The operational flow of the PLCAM is illustrated in Figure x2.1. First, a learner uses an ID to log in to the prototypical PLCAM system [**Step (a)**]. After logging in, a learner can use the menu on the index page of the Media Version Base to manually configure the following: 1) the HP setting, 2) the LP setting, 3) browse the content of the LOR, and 4) read the system manual [**Step (b)**]. The PLCAM can automatically detect the **HP** of a mobile device and the current bandwidth of a wireless network, as shown in the "Dynamic Attributes" [**Step (c)**]. Next, a learner can use the "User Preference Configuration" to manually define the data of an **LP**, such as the preferred maximum Delivery Time (DT), presentation ratio of audio and picture, and the preferred priority of picture, etc. [**Step (d)**]. After configuring the HP and LP, a learner can click "(3) browse the content of LOR" in **Step (b)** to browse the contents by the "Category Page" of the Media Version Base [**Step (e)**]. The system will list the learning content stored in the selected categories [**Step (f)**]. A learner can also select interesting learning content to browse its "SCORM metadata" and "Table of Contents" [**Step (g)**]. Consequently, the PLCAM will adapt the chosen content according to the mobile device profile (HP), LP, and the current Bandwidth (B) together, and offer personalized learning content to the learner's mobile device [**Step (h)**].

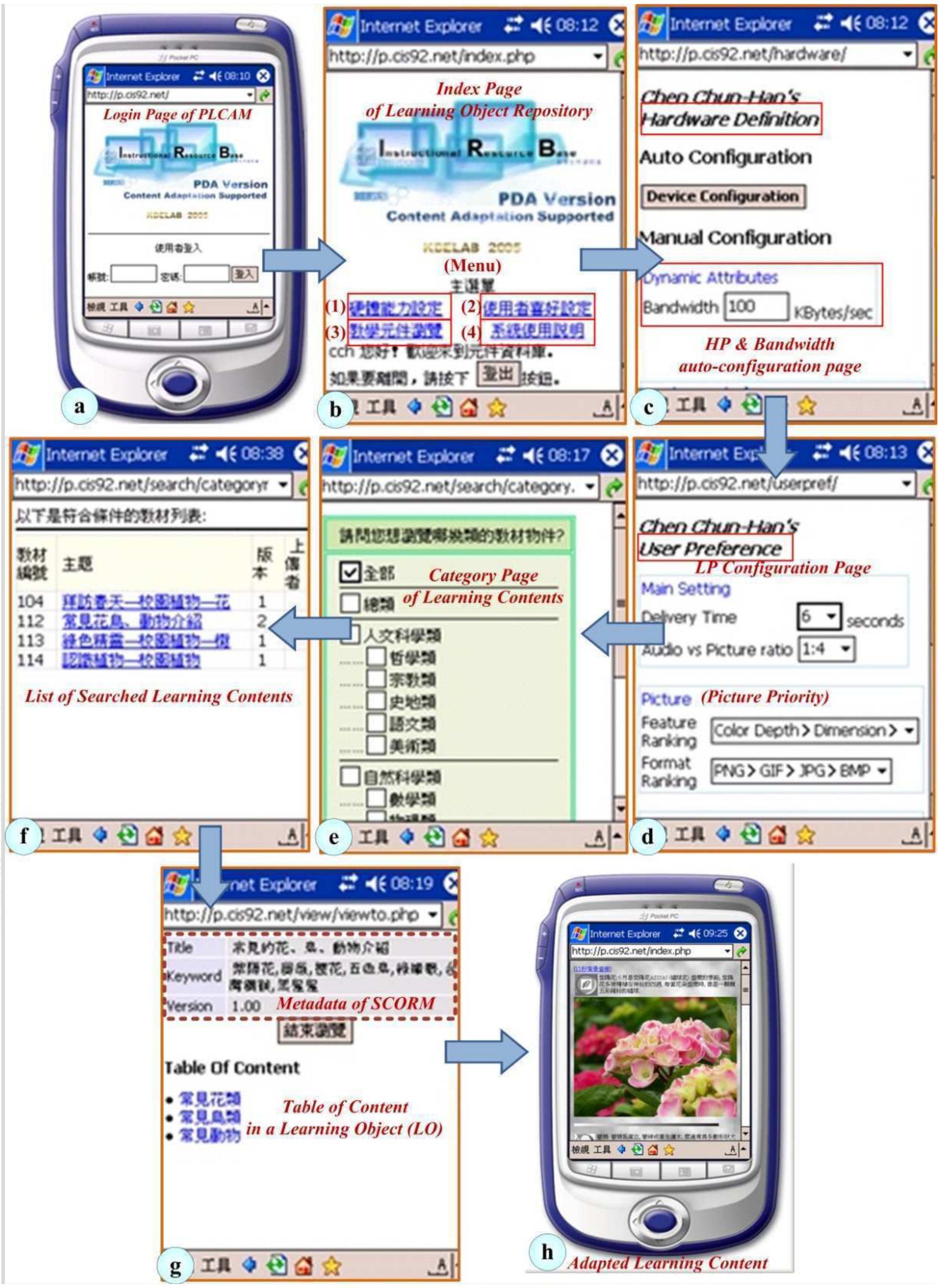


Figure x2.1: Operational flow for a user to retrieve the learning content by the PLCAM system

Figure x2.2 illustrates screenshots of the PLCAM delivering proper personalized adapted learning object content to the similar LR without waiting for the adaptation time of the requested content. Assume there is an existing adapted content version created by LP_a=<5,JGBP,0,0> of learner A, as shown in Figure x2.2.a. This existing version will be selected in advance and delivered directly to the new request with LP_b=<5,JGBP,1,0> of learner B, due to the higher similarity estimation, as shown in Figure x2.2.b. Therefore, learner B does not need to wait for the adaptation to take place again. In the meantime, the PLCAM will prepare an accurate content version with a background picture to meet LP_b=<5,JGBP,1,0>, which is stored in the Media Version Base for the next similar request. For example, this prepared version of LP_b can be delivered directly to meet the new LP_c=<5,JBGP,1,0>, as shown in Figure x2.2.c.

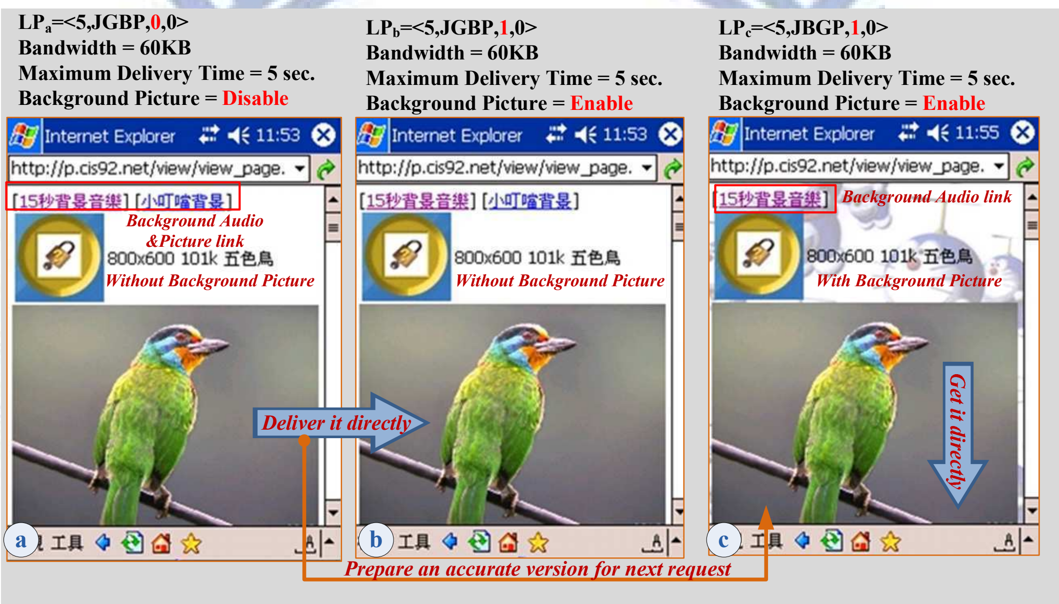


Figure x2.2: (a) Adapted content version of LP_a; (b) delivered the adapted content version of LP_a for LP_b due to the higher similarity; and (c) delivered the content version created by LP_b in advance for LP_c

Figure x2.3 shows several experimental screenshots of the PLCAM system executed on a PDA according to diverse user needs. Figure x2.3.a and Figure x2.3.b illustrate adapted content based on the same HP and LP with different adaptation parameters under different bandwidth values, respectively. The attributes of the LP and HP can be extended to meet the various requirements. Thus, a new attribute in the LP, called *Preferred Picture Property Ordering* (**PPPO**), includes three properties: Dimension (D), Color Depth (C), and Quality (Q). This attribute is used to define the learner's preferred order of image properties. For instance, like the attribute PPFO, a string, DQC, denotes that the order of image priorities is D > C > Q. Hence, we added the PPPO attribute into the LP and changed several parameters, e.g., Delivery Time (DT) and Audio Switch (AS), to test the results of the learning content adaptation process. As shown in Figure x2.3.c, according to the new LP setting and original HP, the property of the picture was changed and the audio, background picture, and icon were replaced by hyperlinks with annotation text. We further evaluated the learning content adaptation capability by changing the screen's horizontal size and color depth of the HP while using the same LP in Figure x2.3.c. The desired adapted learning content was delivered by the PLCAM system, as shown in Figure x2.3.d.

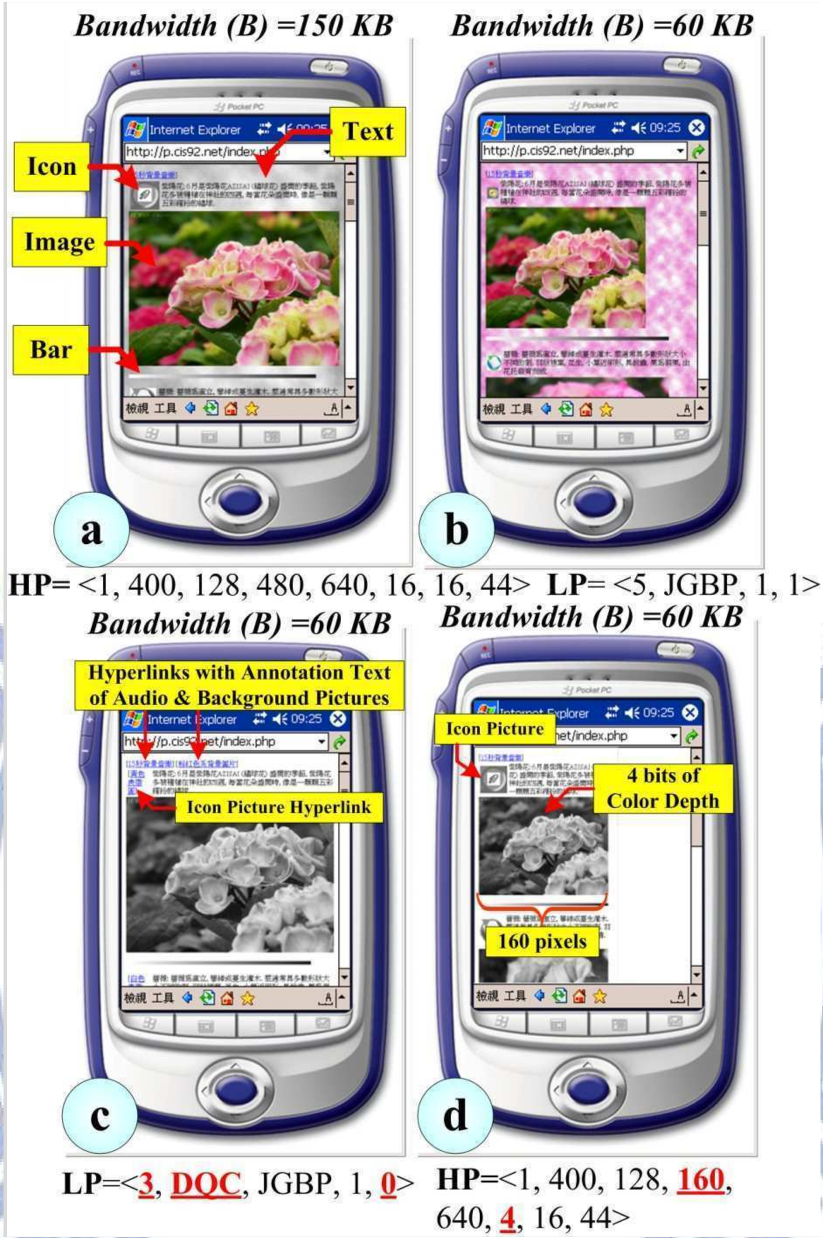


Figure x2.3: Screenshots of the learning content adaptation process performed by the PLCAM system

The PLCAM system also includes a monitoring interface of the LCAMS Web server, used to monitor the latest system status and maintain the CADT. As shown in Figure x2.4, the "Assign Cluster Label" function button can be used to perform the Content Version Clustering Algorithm (*CVClustering*) for grouping the historical block-level nodes into several clusters according to the learners' LPs, where the resultant clustered information of the *CVClustering* will be shown in the bottom-left part of Figure x2.4. Furthermore, the CADT can be reconstructed by the “Rebuild Decision Tree” function button. Its graphical presentation and rule-based representation will be automatically shown in the top-left part of Figure x2.4. The right-hand side of Figure x2.4 will list all of the nodes.

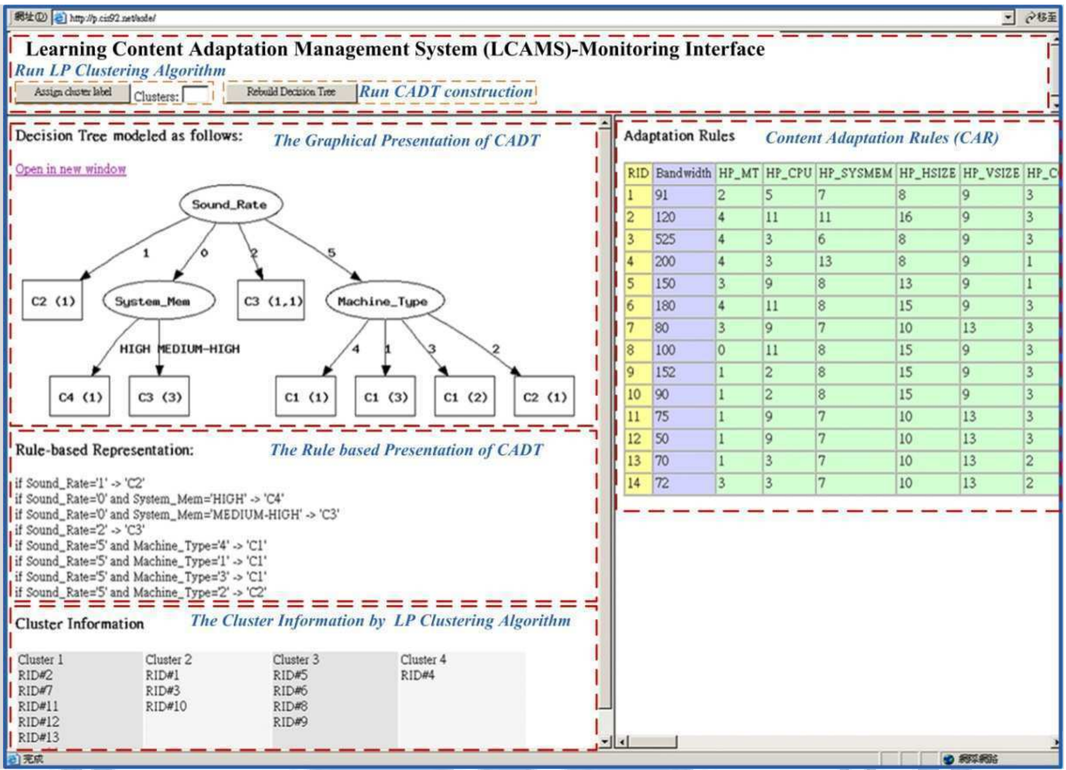


Figure x2.4: Monitoring interface screen of the LCAMS Web server in the PLCAM system

Appendix 3. Online Portfolio Assessment and Diagnosis Scheme

In order to evaluate the effectiveness of the OPASS, the prototypical system has been developed, as shown in Figure x3.1. The OPASS system consists of three databases: (1) Assessment Knowledge Base; (2) Diagnosis Rule Base; and (3) Assessment Portfolio Database. The assessment knowledge can be defined by teachers to meet the requirements of scientific inquiry assessments based on the proposed Assessment Knowledge (AK) definition. The OPASS can be integrated with the Web-based scientific inquiry experiment system based on the proposed connection protocol. Therefore, learners can use the browser to take the scientific inquiry assessment and their operational behavior will be recorded into the assessment portfolio database. After learners finish the assessment, the OAPDP will automatically analyze the assessment portfolio using the rule inference process according to assessment knowledge and then automatically generate personalized diagnostic reports to learners according to diagnostic rules.

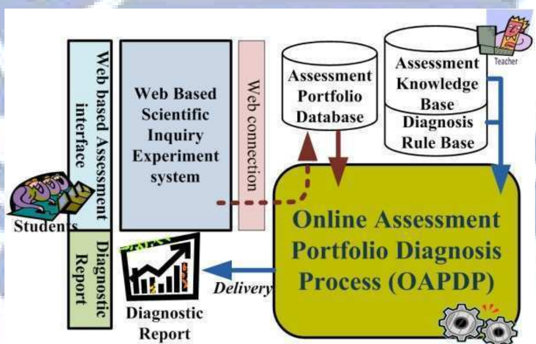


Figure x3.1: Architecture of the Prototypical OPASS

As seen in Figure x3.2, six assessment activities executed on the Web-based scientific inquiry experiment system have also been developed for the Physics (Figure x3.2b) and Biology (Figure x3.2c) experiments, respectively. In Figure x3.2a, each assessment was developed based on the assessment procedure consisting of six steps, where the operation experiment in step 3 offers a Web-based interactive, operational experiment tool to allow learners to operate it and observe responses and reactions.

Figure x3.2: Assessment Activities of the Web-based Scientific Inquiry Experiment in: (b) Physics and (c) Biology Based on (a) Assessment Procedure

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