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# An Adaptive Educational Hypermedia System for Supporting Students in their Traditional Learning Process in Computer Engineering Education*

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Our "information-oriented" society shows an increasing exigency of life-long learning. In such context, the E-Learning approach allows flexibility requested by such kind of learning process. With a plethora of E-Learning providers and solutions available on the market, there is a new kind of problem: the selection of the most suitable E-Learning contents for the various users. In this scenario, Adaptive Educational Hypermedia System can be an effective approach. This paper addresses the design problem of an adaptive educational hypermedia system by the definition of its main components: the user model, the learning content model tracking strategy and the adaptation model are introduced. The proposed Adaptive Educational Hypermedia System has been integrated in an e-Learning platform, Moodle. An experimental campaign has been conducted with interesting results.

**Keywords:** e-Learning; adaptive educational hypermedia system; computer-assisted education

## 1. Introduction

Our society is living a transformation, maybe the most important of the latest years, which, through the strong diffusion of the new information technologies, is radically modifying the nature of the relationships among countries, markets, people and cultures. This technological revolution has clearly facilitated the process of globalization and the information exchange [1, 2].

Information can be considered as an economic good whose value is tightly linked to the amount of knowledge that can give to its users. Gaining new knowledge, competences or skills has determined the need for a continuous update by the actors of the supply chain of the new economy. In fact, in this context, a fundamental service is the life-long learning, or permanent training, which continues all along life and aims at promoting people's fulfilment both at personal and social level. In the learning society—or knowledge society—keeping continuously up-to-date is the essential condition to live in it and follow the changes of our times. In this scenario, the information technologies, the languages, the business management are among the sectors that depend more and more on the on-line training services.

For about twenty years, the 'e-learning' phenomenon has largely spread itself in the distance-learning panorama. This reality reverses the paradigm of the old distance education experiences representing the evolution through the technological platforms. These use the Internet and/or the web and the user's monitoring and tracking procedures perfectly integrating the pedagogical and technological aspect for a dynamic learning [3].

Employing the new tools offered by the Web 2.0, the e-learning gives innovative services that make possible the realization of typical aspects of the 'collaborative learning' and allow the users to have an efficient on-line 'conversation'. The students can leave the old role of users who received information with a top-down approach, to assume a new position of talkers, of people who interact among them creating and exchanging culture [4, 5].

In an e-learning market that is full of several solutions, the choice of an institution or an enterprise of undertaking a process of distance training is obviously not easy. The attention is focused on the development of training models based on two fundamental aspects: pedagogical and technological [6]. In the first case, it is necessary to clearly define how to structure the new training processes and their contents and how to distribute these contents according to the consumer. The technological aspect, instead, aims at creating new tools for the distribution of knowledge that reproduce as much faithfully as possible the pedagogical models for the education [7]. This new dimension could support the teaching activities. In fact, often classrooms are composed by students inattentive or at least bored and wondered. So the question for the teacher is: "Why

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I am not able to reach these students, why they are not excited about the material also if it is presented in an organized and coherent manner?'' This sense of frustration increases when the teacher faces the poor students' performance on tests. On the other hand students can drop out or be hostile about the classroom environment while teacher could become over critical of them starting to question about students' capabilities and to turn the classroom into ''him against them''.

The reason of these difficulties can be in the way of teaching that does not match the way the majority of students in the classroom process information and learn new things. In other words the classroom environment could be incompatible with the students' preferred learning style resulting in stress, frustration and even burnout. There is, in fact, substantial evidence that students learn in a variety of ways and that traditional teaching addresses only a small subset of the learning styles that are in a classroom. As consequence many valuable students lose interest and get low grades in classes, change field and in some cases drop out of school altogether.

In order to change this situation a good solution could be a blended learning approach that combines ''face-to-face instruction with computer-mediated instruction'' [8]. In other words the traditional ''one size fits all'' approach can be effectively supported by adapted distance learning services. In this way the e-Learning can support a new concept of ''teaching'' whose final aim is to increase the quality and effectiveness of the traditional one.

This approach can overcome some problems and stereotypes related to the use of the e-Learning: in fact one of the main criticisms to e-Learning approach is in its lack of interaction among teachers and students. In this way, teachers have a poor control on the students' progresses and attitudes during the formative process. On the other hand, e-Learning platforms can collect a large size of data concerning the student's learning process but this huge quantity of information often can bewilder teachers that evaluate the student's learning trend by the use of little information that can not explain all the aspects of student's knowledge process.

In literature many researchers sustain that an interesting contribution in this field can be furnished by the use of Adaptive Educational Hypermedia System approach that builds an adapting model of the goals, preferences and knowledge of each individual learner [9, 10].

Generally, Adaptive Educational Hypermedia Systems help students in retrieving information that match their preferences by recommending contents or learning services from a large number of candidates, and support people in making decisions in various contexts. In particular, e-Learning platforms can take the most immediate advantage of recommendation facilities, leveraging in different ways user experiences and interactions within the social community to suggest contents of interest [11, 12].

Numerous adaptive hypermedia systems have been designed and implemented over the last fifteen years and these systems can be characterized as first generation, second generation and third generation based on when they were developed and what delivery mechanism was used for deployment of the systems [13–15].

The World Wide Web provided new opportunities for the development of adaptive hypermedia systems: these systems are platform independent and introduce new capabilities as adaptive multimedia presentation, map adaptation and link sorting and provided a better definition of the adaptation techniques in order to provide greater functionality. At the same time user models became more efficient and incorporated more user characteristics [16].

The third generation of Adaptive Hypermedia Educational System removes the problem of the adaptation through one-dimensional, stereotypical user models. These systems incorporate multiple dimensions of the user including expertise, user goals, interests and preferred learning style by subject matter [17, 18].

Another interesting approach is in [19]. This paper describes a model that builds the best students' learning path starting from the analysis of some features outlining their main pedagogical characteristics. This approach is student-centred and students' parameters are selected according to three main factors: the test performance, the time performance and the reviewed topics. The above factors, by the use of an opportune mathematical model, indicate to teachers the learning level achieved by students. By the analysis of these indexes, moreover, it is possible to establish if student can attend the next lesson of the course or needs more support in this part of the learning phase.

The previous described approach is the scenario where this paper is set. In fact, the aim of this paper is the design of an adaptive educational hypermedia system by the definition of its main components. In particular an original tracking strategy for the student's monitoring status during the learning period has been developed and at this aim some indexes able to describe the students' attitude have been introduced in order to easily update the user profile, expressed by the use of metadata standard, and adapt the distance learning path. At the same time a detailed report on students' activities and their main difficulties has sent to the teacher, underlining the main criticisms for each student.

The paper has the following organization: a brief description of Adaptive Hypermedia System is introduced and a more detailed discussion on the student's tracking question is faced. Then the various indexes and the tracking approach are described. In the last section some experimental results are showed.

## 2. The general architecture of an Adaptive Educational Hypermedia System

An Adaptive Educational Hypermedia System (AEHS) is a general framework which aims to personalize, optimize and enforce the student's learning experience by the use of services based on ICT [20]. According to a general definition, reflecting the current state-of-the-art, an AEHS is composed by four main components [21]:

- The Knowledge Space (KS): this component aims to describe and manage the courses' knowledge domains. Usually this component is subdivided into two sub-components: the first one is the Media Space. This module introduces services for the management of the educational resources by the use of descriptive information (e.g. metadata attributes, usage attributes etc.). The second sub-module is the Domain Model. It aims to describe the knowledge domain in hand by the use of graphical formalisms able to represent the topics, their relations and learning goals. In this scenario the use of ontology formalism is an effective way to face the problem
- The User Model (UM): this component has the aim to describe information and data about an individual learner such as knowledge status and learning style preferences. The User Model contains two sub-models: the first one, namely the Learner Knowledge Space, represents the learners' state of knowledge on a topic while the second one, namely the Learner's Cognitive Characteristics and learning preferences, has the aim to represent the learners' preferences. This distinction is needed because the Learner Knowledge Space has to be frequently updated during the interactions between learners and learning objects. On the other hand, the learner's cognitive characteristics and learning preferences has a slower evolution
- The Adaptation Model (AM): this component contains the rules for the description of the runtime behaviour of an AEHS. These rules are usually divided in: Concept Selection Rules and the Content Selection Rules. The first ones select the learner's appropriate concepts from the Domain Model to be covered while the second ones are used for the selection of appropriate resources from the Media Space. In these rule sets the pedagogic and didactic approach of the AEHS is in.
- The Observations Strategy (OBS): the observations, obtained by the use of learners' tracking strategies, are the result of monitoring learner's activities and interactions with the contents and the distance learning's services. Examples of observations are: whether a user has visited a resource, the amount of time spent interacting with a given resource, etc. In general, a learner's tracking strategy is developed in an AEHS. The Adaptation Model can use the information obtained by the observations for the update of the user model.

### *2.1 The proposed knowledge space model*

The knowledge space of an AEHS introduces services for the management of the knowledge domain and educational resources by the use of descriptive information. At this aim a model for the representation of the learning objects is needed. In fact a better definition of leaning resources by the use of their didactic and pedagogical features induces to represent them with a model.

This paper introduces and develops a standardized digest of learning objects in order to better qualify and quantify them. So a vector representation of the learning object is proposed according to this formalism:

***Learning Object* = {*Typology, Ontology,***
***Pedagogical_Educational_Properties,***
***Technical_Requisites, Rights*}**

Each component of the proposed vector is a string vector, which represents a particular feature of the learning resource and collects the most important information obtained combining standard description fields. In fact, the learning contents are usually described by the use of e-Learning metadata standards. One of the most important is the IMS standard for learning object metadata standard [22]. Learning Object Metadata (LOM) is a data model, usually encoded in XML, used to describe a learning object and similar digital resources used to support learning.

The purpose of learning object metadata is to support the reusability of learning objects, to aid discoverability, and to facilitate their interoperability, usually in the context of online learning management systems (LMS). Starting from the metadata description a parser can create a vector structure that allows a better organization of the information related to the learning object and its easier retrieval and management by the use of an AEHS.

In details the descriptive vector's components can so summarized:

- ***{Typology}:*** The main aim of this vector is to furnish a global and general view of the resource. This vector contains all useful information for a general classification of the learning object. The vector *{Typology}* has the following structure: ***{Typology}:= {typology, identifier, title of the resource, author of the resource, date of creation of the resource, language, description, keywords}***
- ***{Ontology}:*** this vector aims to contextualize the resource in the didactic context and in the knowledge domain. Thanks to this vector the AEHS can associate each resource to the course's topics or create learning object's clusters. The vector *{Ontology}* is so structured: ***{Ontology}: {Purpose, Taxonpath, Taxon, Description, Keyword, Relation, Kind, Resource}***
- ***{Pedagogical_educational_properties}:*** this vector describes the resource description from a pedagogical and educative point view. The vector *{Pedagogical_educational_properties}* has the following structure: ***{Pedagogical educational properties}: {pedagogical educational properties, interactivity, resource type, interactivity level, semantic density, resource users, teaching context, age range, difficulty, learning time, description, language}***
- ***{Technical_Requisites}:*** this vector describes the technical requisites for the correct resource's use. In particular, it is engaged in defining what its technological format is, what operating system makes it working, and what kind of application is needed for its correct utilization. The vector *{Technical_requisites}* is so structured: ***{Technical_requisites}:{Technical requisites, format, size, allocation, required software resources, required software resources in detail, duration}***
- ***{Rights}:*** This vector describes the billing modes and the costs associated with the resource. The vector *{Rights}* is so structured:***{Rights}:={Rights, cost, copyright, rating}***

Each components previously introduced can be expressed by the use of IMS LOM fields and more in general can be obtained through the analysis of the metadata associated to the learning object. In this way the system can work with a well-defined set of standard information.

### *2.2 The proposed user model*

The runtime behaviour of an AEHS is deeply influenced by the definition of the user model. In particular the learner's learning characteristics influence the selection of concepts from the domain model, so the definition of the concept selection rules, as well as the selection of appropriate resources, so the definition of the content selection rules. In literature there are many definition of user model and first of all a difference between user profiling and user modelling has to be introduced [23, 24].

A user profile is a collection of variable personal information that represents cognitive skills, intellectual abilities, intentions, learning styles, preferences and interactions with the system. An adaptive system acts according to user model: with no knowledge about the user, a system would perform in the same way for all users. The design of the student model that we will adopt in this paper is described in [25] and forecasts a quintuple of features for the description of the learner's profile. This model takes into account the learner's learning style, background knowledge and preferences by the use of the following parameters:

- *Format* ($f$): type of media the learner prefers to study a learning resource
- *Bandwidth* ($b$): the type of link used by the learner to connect to the internet
- *Interactivity* ($i$): the level of interactivity used by the learner to interact with the learning resource
- *Difficulty* ($d$): the level of preparation of the student
- *Time* ($t$) the time of study the learner spends to study a lesson

These parameters are strictly related to the IMS Learner Information Package (LIP) metadata standard [26]. Learner Information is a collection of information about a Learner (individual or group learners) or a Producer of learning content (creators, providers or vendors).

The IMS Learner Information Package (IMS LIP) specification addresses the interoperability of internet-based Learner Information systems with other systems that support the Internet learning environment. In this paper the features of the proposed user profile model are a digest of the IMS learner profile and assume values in the range [1, 10] coherently with the standard.

When a user model is developed an important task to accomplish is the model initialization. In this paper the initialization phase is structured in the following way: at the course start the following questionnaires have to be submitted to each student: the Index of Learning Style (ILS) questionnaire, an assessment questionnaire on the main topics of the course and a learner's generic information questionnaire. The ILS questionnaire assesses the learner preferences according to four dimensions (active/reflective, sensing/intuitive, visual/verbal and sequential/global) of a learning style model and it was designed by Richard M. Felder [27]. As previously said the ILS approach furnishes information about the learning style by the use of four dimensions.

The first dimension is said sensing/intuition. Sensing learners tend to like learning facts and to be patient with details and good at memorizing facts and doing hands-on work. Intuitive learners often prefer discovering possibilities and relationships and may be better at grasping new concepts and are often more comfortable with abstraction and mathematical formulation than sensing users.

The second dimension is said active/reflective. Active learners tend to retain and understand information best by doing something active with it—discussing or applying it or explaining it to others. Active learners tend to like group work more than reflective learners, who prefer working alone. Reflective learners prefer to think about it quietly first. ''Let's try it out and see how it works'' is an active learner's phrase; ''Let's think it through first'' is the reflective learner's response.

The third dimension is defined sequential/global. Sequential learners tend to gain understanding in linear steps, with each step following logically from the previous one. Global learners tend to learn in large jumps, absorbing material almost randomly without seeing connections, and then suddenly ''getting it.''

The fourth dimension is defined visual/verbal. Visual learners remember best what they see, pictures, diagrams, flow charts, time lines, films, and demonstrations. Verbal learners get more out of words—written and spoken explanations. Starting from the ILS information, a matching strategy among the obtained data and some parameters defined in the IMS LIP model has been developed. In particular, from the active/reflective dimension the preferred interactivity level for the student has been extracted. Then, from the visual/verbal dimension the type of media preferred by learner has been extracted.

In order to complete the student model, further information is necessary. In particular, the model needs to know the starting knowledge level of the learner, how much time he/she usually spends to study a lesson, and so on. This information cannot be obtained with only the learning style, but should be considered separately. In particular the difficulty level parameter can be obtained by the use of an assessment questionnaire.

This test allows the acquisition about the learner's starting competence and defines the student's starting difficulty level. While the other information, bandwidth and time of study are collected by the use of the general questionnaire. The complete student model is characterized in Table 1.

### *2.3 The observation phase: a tracking strategy proposal*

In an AEHS the observation module has the aim to track and collect information during the students' learning activities. In this section the description of an approach for tracking the students during their learning activities is furnished. An effective design method for students' tracking has to furnish detailed information to teachers allowing them more efficacious evaluation students' progresses. The two main aims of the proposed approach are:

- to maintain up-to-date information about student model's parameters. The information observed during learner's activity studying are:
  - the studying time: this parameter evaluates the average of time used to study a learning resource and time for the first repetition
  - the student's level of knowledge
  - the student's interest for well defined kind of media
- to provide an evaluation of the learner action related to his entire learning path by the use of information acquired during the observation activity. In this way it is possible to evaluate the learner performance by providing a global assessment not based only on the final test grade.

By denoting with the subscript $u$ the information related to the student and with $r$ the information related to the learning resource, it is supposed to know some parameters that tutor initially sets:

- the studying time of the k-th learning resource: $T_r^k$
- a time parameter $T_x$, generally expressed as percentage of $T_r^k$, that measures the maximum shift from the $T_r^k$ defined by the teacher. This parameter have to be greater than zero
- the minimum threshold grade $v_r$ for that learning resource.

**Table 1.** User Model Structure

| Type of media | Interactivity level | Bandwidth | Difficulty level | Time of study |
|---|---|---|---|---|
| ILS (Visual/ Verbal) | ILS (Active/ Reflective) | General Questionnaire | Assessment Questionnaire | General Questionnaire |

The parameter $T_{uk}$, the time spent on the k-th learning object, has to be matched with the reference learning time $T_{rk}$. This matching is accomplished by using an appropriate rational function $G_t$:

$$G_t = 1 + N + \frac{(T_u^k - T_r^k)^2 - T_x^2}{(T_u^k - T_r^k)^2 + \frac{T_x^2}{N}} \tag{1}$$

The goal of this function (1), that assumes value in the range [0, 1], is to evaluate the student's approach to the learning time. Little values of the $G_t$ function mean that the proposed learning object is suitable with the learning time approach of the student while big values mean a not correct approach to the study of the learning object by student and it is an alarm signal for the teacher. The parameter $D_r^k$ allows taking in account the learning object's difficulty level and so giving more studying time in the case of difficult resources. When $G_t$ shows low values, under a threshold fixed by teacher, the user's profile has to be updated. Moreover the tracking module is able to take into account how many times the student repeats the same lesson. This occurrence is considered by evaluating the function:

$$T_k(i) = \frac{1}{1 + a(i-1)} \quad \in \,]0, 1] \tag{2}$$

where $i = 1, 2, 3, \ldots$ counts the number of repetitions of the same lesson and in this way $T_{u^K}$=$T'_{u^K}$ * $T_K(i)$. The function (2) has a hyperbolic progress that assumes the maximum value when $i = 1$ and decreases when $i$ increases. The parameter a sets the decrement rate and is equal to:

$$a = \frac{d_u}{2d_r} \tag{3}$$

In this way, if the resource is more difficult than the learner preparation level, the decrement rate does not heavily penalize the learner, and vice versa.

The second target of the tracking module is providing a student evaluation that does not involve only the grade obtained at final test but by the use of all information acquired during the student's learning activity. To this aim, the learner assessment is evaluated taking into account two terms: the first is relative to the present state activity and a term relative to his past learning activity. The student assessment evaluation function is so defined:

$$\begin{aligned} Score_k = \mu \frac{v_k}{v_{max}} \left( (1-\alpha) \bullet \left( \frac{Sgn(G_v) + 1}{2} \right) + \alpha \bullet \frac{T_k(i)}{G_t} \bullet \left( \frac{1 + Sgn(D_r^k - D_u^k)}{2} \right) \right) + \\ + (1-\mu) \bullet \left( 1 + \frac{\log_{10}(S_p(Q_k)}{3} \right) \end{aligned} \tag{4}$$

This function (4) is similar in the structure to another one that is used in the computer network field for the management of the packet's transmission in the TCP protocol [28]

The first term

$$A = \frac{v_k}{v_{max}} \left( (1-\alpha) \bullet \left( \frac{Sgn(G_v) + 1}{2} \right) + \alpha \bullet \frac{T_k(i)}{G_t} \bullet \left( \frac{1 + Sgn(D_r^k - D_u^k)}{2} \right) \right) \tag{5}$$

with $G_v = v_k - v_k^r \in \; [1 - v_{max}, \; 1 + v_{max}]$

$$\text{and } V_r^k = 7 - \left( Int\left( \frac{1 + Sgn(D_r^k - 3)}{2} \right) + Int\left( \frac{1 + Sgn(D_r^k - 7)}{2} \right) \right) \tag{6}$$

represents the result obtained in the study of the last learning object. In particular A values 0 when the student has a very low result and 1 when the student has a very good result. The other term

$$B = 1 + \frac{\log_{10}(S_p(Q_k)}{3} \tag{7}$$

takes in account the previous results of the student.

In particular the term

$$S_p(Q_k) = \frac{Q_k}{\frac{1}{k-1}\sum_{q=1}^{k-1} Q_q} \quad \in \left[\frac{1}{v_{max}D_{max}^2}, v_{max}D_{max}^2\right] \tag{8}$$

where:

$$Q_k = v_k\frac{D_r^k}{D_u^k} \quad \in \left[\frac{v_{max}}{D_{max}}, v_{max}D_{max}\right] \tag{9}$$

compares and weights the grade obtained for the actual learning object with the grades obtained in the past. The value $\mu$ is a weight that can be tuned in order to emphasize the A or the B term.

So the score value assumes the following form:

$$Score_k = \mu\frac{v_k}{v_{max}}\left((1-\alpha)\bullet\left(\frac{Sgn(v_k - v_k^r)+1}{2}\right) + \alpha\bullet\frac{\frac{1}{1+\frac{D_u^k}{2D_r^k}(i-1)}}{1+N+\frac{(T_u^k-T_r^k)^2-T_x^2}{(T_u^k-T_r^k)^2+\frac{T_x^2}{N}}}\bullet\left(\frac{1+Sgn(D_r^k - D_u^k)}{2}\right)\right)+$$
$$+(1-\mu)\bullet\left(1+\log_{10}\left(\frac{v_k\frac{D_r^k}{D_u^k}}{\frac{1}{3}\frac{1}{k-1}\sum_{q=1}^{k-1} v_q\frac{D_r^q}{D_u^q}}\right)\right) \tag{10}$$

By analyzing each single element of the $Score_k$ (10) term, we can realize that if $Score_k$ assumes a low value, learner assessment is not fair, and teacher have to support the learner. Otherwise, score value near to 1 he can approach to the next topic forecasted in the learning path. In any case, the student profile parameters are updated. In particular if the learner has a preparation level greater than the $k$-th learning resource's difficulty one, his score assessment is not fair and he fails the final test his preparation level is decreased according to this formula:

$$D_u^{k+1} = \tilde{D}_u^k\bullet\frac{(1-Sgn(\tilde{S}core_k - Score^{thre}))}{2} + \tilde{D}_r^k\bullet\frac{(1+Sgn(\tilde{S}core_k - Score^{thre}))}{2} \tag{11}$$

and if

$$\tilde{S}core_k > Score^{thre} \Rightarrow D_u^{k+1} = \tilde{D}_r^k = \frac{1}{k}\sum_{i=1}^{k} D_r^i \tag{12}$$

Otherwise

$$\tilde{S}core_k < Score^{thre} \Rightarrow D_u^{k+1} = \tilde{D}_u^k = \frac{1}{k}\sum_{i=1}^{k} D_u^i \tag{13}$$

In the same way the learner's learning time is so updated:

$$T_u^{k+1} = \tilde{T}_u^k\bullet\frac{(1-Sign(\tilde{S}core_k - Score^{thre}))}{2} + \tilde{T}_r^k\bullet\frac{(1+Sign(\tilde{S}core_k - Score^{thre}))}{2} \tag{14}$$

and if

$$\tilde{S}core_k > Score^{thre} \Rightarrow T_u^{k+1} = \tilde{T}_r^k = \frac{1}{k}\sum_{i=1}^{k} T_r^i \tag{15}$$

Otherwise

$$\tilde{S}core_k < Score^{thre} \Rightarrow T_u^{k+1} = \tilde{T}_u^k = \frac{1}{k}\sum_{i=1}^{k} T_u^i \tag{16}$$

**Table 2.** IMS-LIP Metadata fields updating related to the assessment information

| Learner metadata fields | Semantic |
|---|---|
| *Activity.evaluation.result.result[i].fieldata = Score*$_i$ | Assessment value relative to the j-th learning resource |
| *Activity.evaluation.result.score = Score* | Assessment value relative to the complete learning path |
| *Goal.status = completed* | Overcoming relative to a learning resource |

At the end of the learning path, the complete learner assessment can be evaluated in this way:

$$\tilde{S}core_k = \frac{1}{k}\sum_{i=1}^{k} Score_i \tag{17}$$

The information updated in the IMS-LIP metadata fields are showed in Table 2.

### 2.4 The proposed adaptive model

In [6] two distinct areas of adaptation are distinguished: content level adaptation or adaptive presentation and link level adaptation or adaptive navigation support. This paper is focused on the design of an adaptive presentation model by starting on learners and learning resource's information profile. In particular, the proposed model is developed in three main steps:

***Step 1: evaluation of functions for the matching between student and learning profile:*** these functions aim to match the learners' parameters with the relative learning objects description parameters. The proposed functions express the minimum value when there is the best matching for the considered parameter, otherwise the resource parameter is not close to learner. The functions are:

$$\textit{Interactivity: } M_I = 1 + |I_r - I_u| \in [1, 10] \tag{18}$$

$$\textit{Difficulty: } M_D = 1 + |D_r - D_u| \in [1, 10] \tag{19}$$

$$\textit{Type\_of\_Media: } M_F = 1 + |F_r - F_u| \in [1, 10] \tag{20}$$

$$\textit{Time\_of\_Studying: } M_T(T_r, T_u) = 11 + Int\left(\frac{(T_r - T_u)^2 - 10^2}{(T_r - T_u)^2 + 10}\right) \in [1, 10] \tag{21}$$

$$\textit{Bandwidth: } M_B = 5(1 - Sign(B_u - B_r + 2)) \in [0, 10] \tag{22}$$

***Step 2: Evaluation of similarity functions:*** once the matching functions are evaluated, the educational $C_e$ and $C_t$ technical similarity functions can be considered. To this end a normalized weighted average mechanism is considered:

$$C_t = \sqrt{M_F(F_r, F_u)^2 + M_B(B_r, B_u)^2} \in [1.10\sqrt{2}] \tag{23}$$

$$C_e = \sqrt{M_T(T_r, T_u)^2 + M_D(D_r, D_u)^2 + M_I(I_r, I_u)^2} \in [\sqrt{3}, 10\sqrt{3}] \tag{24}$$

These functions express the closeness of the resources to user profile both from the point of view of technical parameters both from the point of view of educational parameters.

***Step 3: Evaluation of the global matching index:*** the final step is the evaluation of the distance between the learner and the learning resources in term of educational and technical characteristics. To this aim, the global index *Ind* is so calculated:

$$Ind = \sqrt{C_t^2 + C_e^2} \in [2, 10\sqrt{5}] \tag{25}$$

In this way, the minimum value of *Ind* defines the nearest learning resource to the learner characteristics, namely:

$$Ind_{OPT} = \underset{i}{Min}\ Ind_i \tag{26}$$

In Fig. 1. the full schema of the proposed tracking and adaptation model.

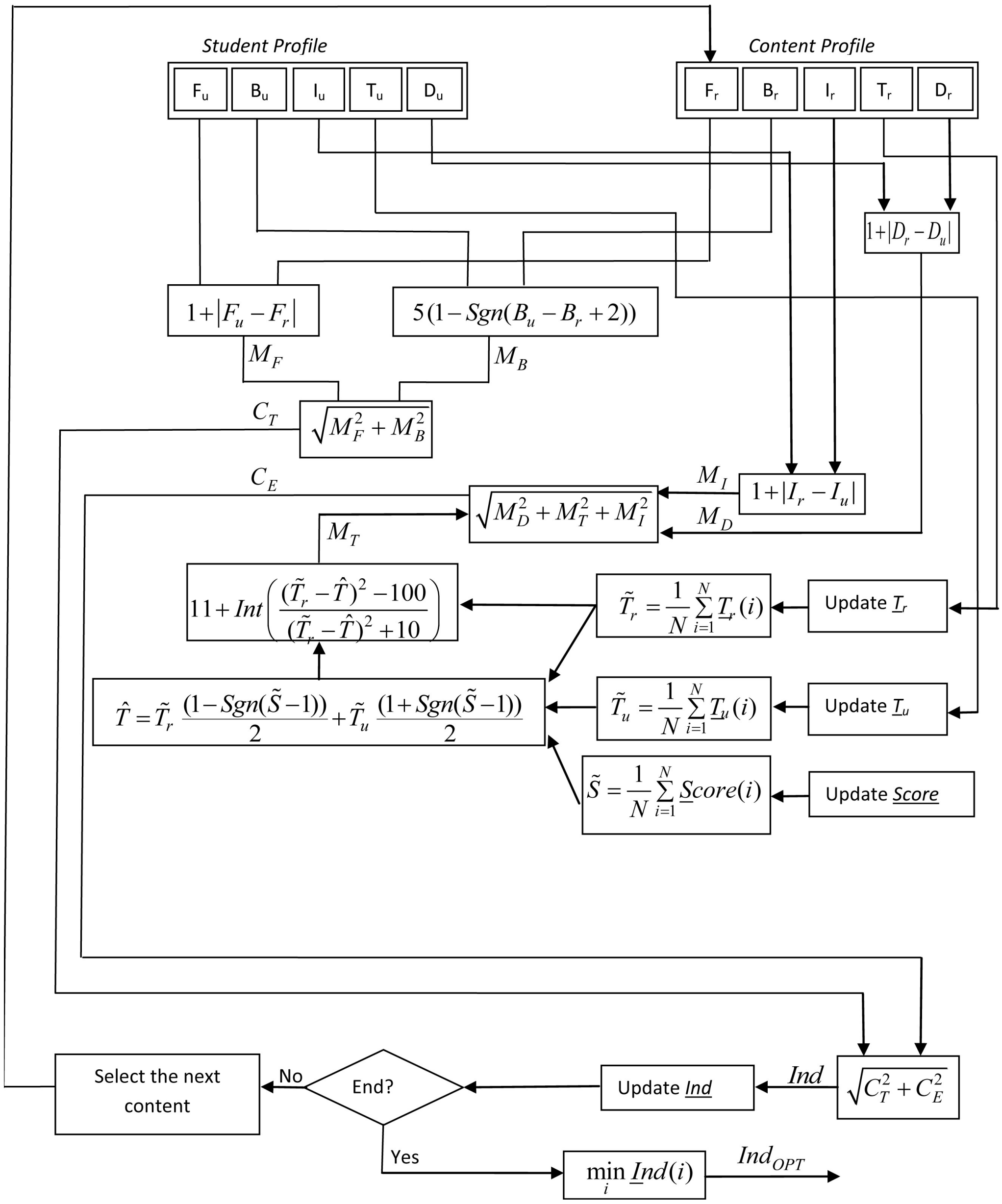


**Fig. 1.** The tracking and the adaptive model of the proposed Adaptive Educational Hypermedia System.

## 3. Experimental results

In our experimentation we have considered three different blended courses in the field of Computer Science: Introduction to Computer Science (about 500 students), Computer Networks (about 100 students) and Software Technologies for the Web (about 150 students) belonging to the school of Engineering and a comparison with traditional approaches has been conducted. For each of this course we used a dataset composed by one hundred descriptions, according the model previously described, of learning objects that we teachers created or retrieved in Internet.

Obviously the learning objects belong to various modules according to the ontology model developed by teachers. At the same time, they described the profile of their classes according to the model previously introduced.

The proposed AEHS has been introduced, as plug-in, in the E-Learning Platform named Moodle [29]. An assessment test has been submitted at the beginning of the lectures and at the end of each topic an evaluation test has been submitted. In particular the course model was the following: traditional lectures and students' support by the use of contents suggested by the proposed approach. At the end of the courses we measured the

**Table 3.** Obtained results (the maximum Knowledge Level value is 10)

| | Introduction to Computer Science 2014 | Introduction to Computer Science 2015 | Computer Networks 2014 | Computer Networks 2015 | Software Technologies for the Web 2014 | Software Technologies for the Web 2015 |
|---|---|---|---|---|---|---|
| Starting Knowledge Level | 3.3 | 3.9 | 4.1 | 4.2 | 4.1 | 3.9 |
| Final Knowledge Level | 6.9 | 8.2 | 7.3 | 8.8 | 6.9 | 8.3 |
| Improvement | 3.6 | 4.3 | 3.2 | 4.6 | 2.8 | 4.4 |

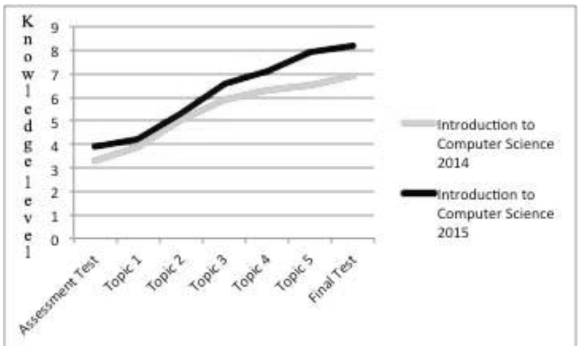


**Fig. 2.** Comparison of the Average learning knowledge reached by the classrooms Introduction to Computer Science 2014 and 2015 during the learning activities.

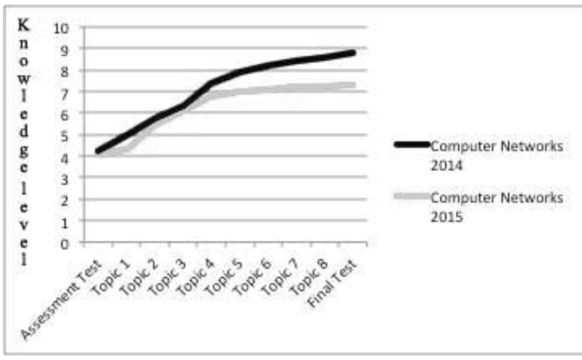


**Fig. 3.** Comparison of the Average learning knowledge reached by the classrooms Computer Networks 2014 and 2015 during the learning activities.

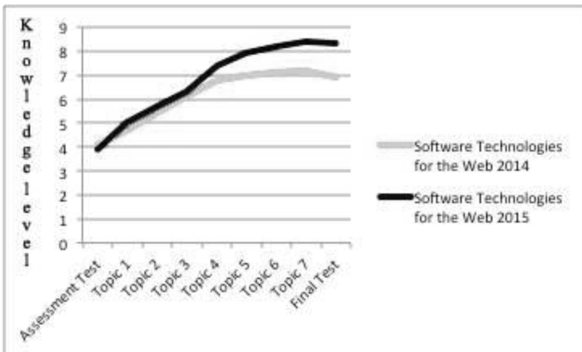


**Fig. 4.** Comparison of the Average learning knowledge reached by the classrooms Computer Networks 2014 and 2015 during the learning activities.

average knowledge level of students by an assessment test. At the same time we compared the values with the other ones obtained one year before with the same courses.

In particular the courses used the same learning contents and a course model based on traditional lessons and by the use of a normal Moodle platform. The obtained results are depicted in Table 3.

In particular, Figs. 2, 3 and 4 express the average knowledge level gained by the students during the learning activities.

As we can see the obtained results show as the proposed approach increase the knowledge level and improve the learning approach of students: the students' performance of 2015 was better than the one obtained by the students the previous year and shows the success of this approach.

## 4. Conclusion

In this paper we showed an AEHS based on the definition of a set of features related to the concepts, skills and attitudes the student is expected to assimilate by the end of a unit. Each feature is represented by means of appropriate mathematical functions, which are combined in a mathematical model devised to facilitate the course characterization and comparison and to provide support for diagnostics.

In the paper we showed the design and implementation of a software module for deducing the representative "vector" of a given student starting from the standard description of various resources (student profiles, content descriptions and so on) and for the adaptation.

We discussed experimental results in using the quoted vectors to find the most suitable set of contents for each student profile and we proved its effectiveness in some real cases.

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