Using Tracking Data to Build Student and Group Models and Generate Advice in Web-Based Distance Learning Environments[1]

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Abstract. Web-based distance education enables courses to be delivered to a large number of geographically distributed students. However, many studies report that the lack of communication with tutors and peers, and the limited feedback from course facilitators, can lead to drawbacks such as students feeling isolated and disorientated. Instructors play a lead role in managing courses and dealing with reported problems, and they need to have a good understanding of what is happening in distance classes. Although Web Course Management Systems (WCMS), which are the most common platform for on-line learning, collect a vast amount of tracking data, there is a lack of automatic features to analyse this data and to use it to support course facilitators. This paper proposes an approach where tracking data from WCMS is analysed to build fuzzy student and group models. These models are used to generate advice informing facilitators about problems and needs of individuals and groups of students, as well as suggesting appropriate actions, where possible. We will present a prototype of a Teacher Advisor [TADV] that illustrates the approach. An empirical evaluation of TADV has shown that it provides practical and effective advice, allowing advice generation and informing of instructors, which, in turn, makes it easy to send help and feedback to distance students. Instructors confirmed the suitability of generated advice and appreciated the knowledge they gained about their students. The students appreciated the feedback received from the instructors as a result of TADV recommendations. The study showed better overall satisfaction and social aspects for the students who used TADV advising features.

Keywords: (Semi)automatic advice generation, Analysis of tracking data, Fuzzy student and group modelling, User modelling for web-based distance learning, Intelligent learning management systems.

1. Introduction

Distance education programs are conducted in many different ways, and have seen rapid improvement in recent years. Given the availability of resources such as the Internet, computer networks, e-mail and other collaborative tools, it seemed feasible to enhance the educational outcomes of such programs. The Web-based implementation of distance courses allows delivery to a greater number of students and eliminates the problems of distributing software to individuals. In addition, Web-Based distance education (WBDE) offers many features that benefit the educational process over other distance education delivery methods. However, problems and barriers in distance courses delivered on the Web have been reported, such as the students' feeling of isolation and disorientation in the course hyperspace, facilitators' communication overload, and the difficulty in addressing the needs of each individual student (Galusha, 1997; Rivera and Rice, 2000).

In WBDE environments, students need to know how to actively gain knowledge and to effectively communicate and work with teachers and peers. Teachers no longer follow a traditional teacher-centered education, instead becoming facilitators who support and guide the students' learning (Galusha, 1997). They are required to carefully monitor students' progress throughout the course, get an understanding of the problems that each individual student, or groups of students, and provide appropriate help and guidance. For this, teachers need to have appropriate information about the knowledge status and the communicative

[1] This paper (or a similar version) is not currently under review by a journal or conference, nor will it be submitted to such within the next three months.

behavior of their students. Based on advances in the technologies used to build educational software, especially the use of Artificial Intelligence techniques, we believe that Web-based distant courseware and learning management systems can be enhanced to support students and facilitators in distance education environments.

Web Course Management Systems (WCMS) are popular tools designed to support authoring, delivery, and management of WBDE programs. However, they provide limited support to the facilitators to monitor what is happening in distance classes (Kosba et al., 2004). Usually, they keep a vast amount of data collected through the tracking of students' interactions, such as the their logins, visited pages, time spent on course pages, scores achieved in quizzes, postings to discussion forums, etc. This tracking data is used by WCMS reporting features to generate some statistical reports to provide facilitators with information about students' interactions. However, these reports are usually presented in a complex format, which is often incomprehensible and difficult to use. In WCMS environments, the facilitators often face difficulties in monitoring and understanding cognitive and social problems experienced by students (Mazza & Dimitrova, 2004). The majority of the available such systems are not equipped with intelligent mechanisms to allow instructors to monitor the students' performance. Even by using the statistical reports, it is difficult for instructors to find an automatic way to guide and advise students. Accordingly, facilitators usually receive many enquiries from distant students, e.g. through e-mails, chat rooms, and discussion forums. Often, facilitators may fail to guide or advise students effectively due to insufficient information they have about the students' behaviour, and knowledge status of both individual students and groups of students.

Recently, intelligent techniques have been used to enhance WCMS (Calvo & Grandbastien, 2003) but, in line with most AIED systems, c.f. Brusilovsky (1999), the effort is focused mainly on providing adaptive help to students. There is a lack of automatic features to guide instructors, by pointing at important situations and highlighting possible problems. In this paper, we propose a framework, called TADV (Teacher ADVisor), which uses the tracking data generated by WCMS to build student, group, and class models, and generates advice to facilitators to help them manage distance classes effectively.

The architecture of the TADV framework is discussed in Section 2. In Section 3, the components of the courseware structure recommended for TADV are outlined. The techniques used for student and group modelling are presented in Section 4, and the TADV advice generation mechanism is explained in Section 5. The TADV prototype implemented to validate the framework is described in Section 6. An empirical study conducted to evaluate the prototype is discussed in Section 7. Finally, in Section 8, the contributions of our work are pointed out by comparing with related work.

2. Overview of the TADV framework

The TADV framework proposes an extension of traditional WCMS with intelligent tools that analyse student tracking data, build models of individual students, groups and the class, and use these models to inform the facilitators of what is happening in their classes and suggest possible activities. Figure 1 illustrates the role of TADV and shows its architecture. PART-I in the figure (in grey background) represents the conventional procedure performed by an educational organisation to build and use a WCMS course; PART-II (in white background) represents the extension of WCMS provided by TADV.

PART-I represents a conventional procedure for developing a course with WCMS, which is commonly followed in distance learning: the teacher prepares the pedagogical content, represented in a Domain Knowledge Base (DKB), defines the navigational structure, and assigns the discussion forums for interactions on the content. The students normally access the course via a web browser. Information about the students registered on the course is kept by WCMS in a Student Database (SDB). SDB also accumulates tracking data about both students' interactions with the course material and participation in discussion forums. PART-I is outside the focus of this paper, the reader is directed to Kosba (2005) for a more detailed description of the main components in a WCMS.

PART II represents the extension of traditional WCMS proposed by TADV. Metadata about the learning materials and domain concepts is provided in a Domain Meta-Knowledge (DMK), which is a key source for reasoning about the students' behaviour. Section 3 provides more details about DMK. A key component in TADV is the Student Model Builder (SMB) that analyses the WCMS tracking data and builds individual Student Models (SM), Group Models (GM), and Class Models (CM). The structure of these models, together with the algorithms used for their elicitation, is discussed in Section 4. Another major component in TADV is the Advice Generator (AG) that uses SM, GM, CM, and a set of predefined conditions, to identify appropriate advising situations and to generate pieces of advice to be sent to the teacher. The advice generation mechanism is described in detail in Section 5.

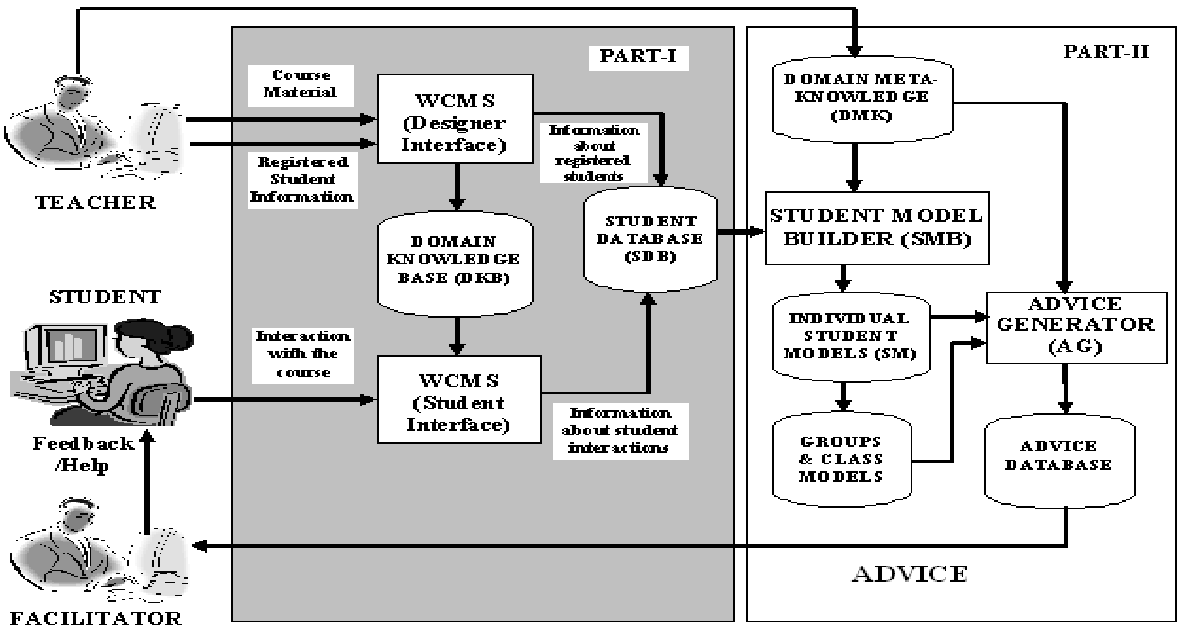

Figure 1. TADV is an extension of a conventional WCMS. PART I presents the components of a conventional WCMS. PART II represents the TADV architecture.

3. Courseware Structure and Meta-Knowledge

In line with the recent move towards interoperable semantic-aware learning systems (Anderson & Whitelock, 2004; Aroyo & Dicheva, 2004; McCalla, 2004), TADV considers that the course material is annotated by following established meta-data standards, see Duval (2004). This not only allows for reasoning about the students' behaviour but also ensures domain and course independence of the TADV components.

TADV requires the course material to be organized as a set of learning objects (HTML pages, presentations, video clips, simulations, etc.) that include the body of the knowledge representing the course and are defined by following the IEEE LOM metadata standard (IEEE 1484.12.1-2002). The schema used, proposes some attributes selected from three categories (General, Technical, and Educational), a subset of the nine categories defined by IEEE LOM standards.

TADV is suited for courses with a conventional hierarchical structure. A course is divided into a set of **L**essons ($L=\{l_1,l_2,\ldots,l_n\}$), e.g. chapters, sections, parts. The knowledge building blocks in a lesson are called concepts, e.g. $C_i = \{c_{i1}, c_{i2}, \ldots\ldots\ldots .c_{ip}\}$ is the set of **C**oncepts contained in the i^{th} lesson. The following sets are associated with each concept c:

- **Learning objects** represent the material used to explain the concept to the students; we will denote the set of learning **O**bjects related to concept c with $O_c = \{o_{c1}, o_{c2}, \ldots\ldots o_{ck}\}$.
- **Assessment quizzes** contain the questions or quizzes used to assess the student's level of understanding of the concept; we will denote the set of assessment **Q**uizzes used to assess concept c with $Q_c = \{q_{c1}, q_{c2}, \ldots\ldots q_{cl}\}$.
- **Communication activities** represent the discussion forums and chat-rooms created to discuss concept; we will denote the set of **D**iscussion forums created to discuss concept c with $D_c = \{d_{c1}, d_{c2}, \ldots\ldots d_{cm}\}$.

DMK possesses the information that describes the course material and how it is inter-related. Concepts in a domain are usually related to one another in various ways. Therefore, most authors of intelligent educational systems use hierarchical structures to link the parts of the domain knowledge, see for example (Goodkovsky, 1996; Specht et al., 1997; Capuano et al., 2000). Such links may be of the same type (e.g. prerequisite) or they may have more than one type of relationship (e.g. part of, type of, etc.). Teachers and course designers who use WCMS to build Web-based distance courseware usually do not consider the tasks of representing the relationships between domain concepts. This is because WCMS hardly allow intelligent features (Chang, 2003). In addition, it is unlikely that teachers can be familiar with knowledge representation techniques, which are usually difficult and time-consuming tasks. Our approach in TADV is to simplify this process by building a "concept map" that shows the relations among domain concepts in terms of the level of necessity of other concepts for understanding each separate concept. The concept map shows the prerequisite hierarchy between the course concepts. This approach is to some extent similar to the approach used by Goodkovsky (1996) to represent relations between domain concepts. In TADV, three types of relations are defined between domain concepts:

- S – Strongly related: c_1 is strongly related to c_2, denoted by (c_1, c_2, Strong), if c_1 is a prerequisite of c_2, and to know c_2, a student should completely understand c_1.
- M – Moderately related: c_1 is moderately related to c_2, denoted (c_1, c_2, Moderate), if c_1 is a prerequisite to c_2, and to know c_2, a student should have some understanding of c_1.
- W – Weakly related - c_1 is weakly related to c_2, denoted (c_1, c_2, Weak), if c_1 is a prerequisite to c_2, and, although the two concepts are related, a student can understand c_2 without completely understanding c_1.

Figure 2 shows a part of the concept map for a lesson on Functions in a Discrete Mathematics course. The arrows show prerequisite relations that can be S, M, or W. The concept map is used by the Advice Generator (AG) to infer why a student or a group of students may face problems with a specific concept (see Section 5 for a description of the advice generator in TADV).

There are four levels in the course structure: course level, lessons level, concepts level, and content level. Course metadata include descriptive information, such as the course identification code, name, description, etc. Lesson metadata include the lesson identification, name, description, and objectives. For the course concepts, DMK includes information, such as concept identification (name, description, etc.). DMK also includes information that represents the types of relations between the concepts, as discussed above. The course calendar should be prepared by course facilitators to determine the interval of time assigned for each group of concepts and also the time dedicated for each individual concept. The purpose of including calendar information is to organize the course period to the distant students. It is used in TADV to identify delays in the students' progress.

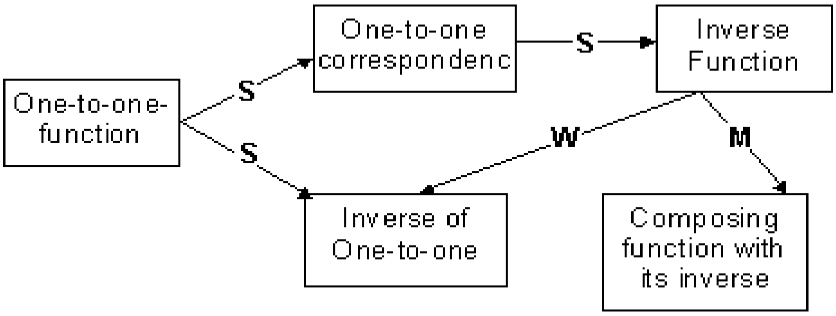

Figure 2. Part of the concept map from the "Functions" lesson in a Discrete Mathematics course.

In addition to the attributes described above, which are all existent in IEEE LOM, TADV introduces some meta-data attributes that are required for the fuzzy student and group modelling approach, as described in the next section.

4. Student, Group, and Class Modeling in TADV

TADV considers cognitive and behavioural aspects of individual students, groups, and the whole class. Both aspects are combined and taken into account when advice is generated. The cognitive characteristics concern the students' knowledge status, represented as *overlay* upon the domain knowledge. An approach of approximate student modelling based on *fuzzy techniques* and *certainty factor theory* is adopted. The behavioural aspects are monitored to identify the students' preferences, including their interaction style. The structure of the student, group, and class models in TADV, together with the diagnosing mechanism employed, are described in this section.

4.1 Individual student models in TADV

A student model in TADV represents an individual student and comprises of four parts:

- Student Profile Model - stores general information about the student, such as personal details, educational background, overall performance, etc.
- Student Behaviour Model - records the student's learning interactions, such as the sessions the student has gone through, and detailed information of his/her activities. Examples of this information include learning objects visited, assessment quizzes attempted, communication activities the student has taken part in, elapsed type of each access, interaction activities performed (reading text, solving problem, posting question or comment in a discussion forum), and scores achieved in quizzes.

- Student Preferences Model - presents the student's preferred types of learning objects, assessment quizzes, and communication activities, and is based on a summary of the student's activities throughout the course.
- Student Knowledge Model (SKM) - indicates the student's level of understanding of domain concepts. Each concept is associated with a measurement of the student's knowledge status in relation to that concept. The computation of this status is based on fuzzy sets and certainty factor theories (Turban, 1993; Buchanan & Shortliffe, 1997). Accordingly, for each concept *c*, two fuzzy values (ranges from 0 to 1), are calculated: a Measure of Belief, *MB(c)*, that the student understands *c* and a Measure of Disbelief, *MD(c)*, that the student understands *c*. A Certainty Factor, *CF(c)* (ranges from -1 to 1) is calculated to represent the student's knowledge status with respect to *c*. The algorithm used for calculating *MB(c)*, *MD(c)* and *CF(c)* is presented in Section 4.3.

4.2 Group and class models in TADV

One of the distinctive characteristics of TADV is its ability to aid teachers in monitoring the progress of groups and classes (a class is considered as a big group) and to advise on appropriate activities that can improve the group knowledge status and initiate communication activities amongst students. Group models in TADV are used to identify problems that happen to most of the students in a group and to determine how these problems can be related to the characteristics of the students in the group. The instructors can define groups based on the student profiles (nationality, background, overall performance, etc.) or the student preferences (students who prefer reading, discussions, etc.).

A GM in TADV represents the knowledge status and the communicative characteristics of all students in the group. The knowledge status is derived through the aggregation of the individual student knowledge models of the group members. Akin to a SM, a GM is an overlay upon the domain. For each concept *c*, three values are calculated that represent summative measures of the group members' understanding of *c*: a Group Measure of Belief *GMB(c)* that the group as a whole understands *c*, a Group Measure of Disbelief *GMD(c)* that the group as a whole understands *c*, and a Group Certainty Factor *GCF(c)*.

In addition to the knowledge status, TADV combines the behavioural and preference parts of the individual SMs of all members to indicate the most communicative students in the group and those who do not participate in discussions, and to identify beneficial communication activities for members, e.g. advanced students can be encouraged to help their struggling peers or students who do not communicate can be assigned roles in discussion forums (see group advice in Section 5).

The class model in TADV is simply a GM that reflects the status of the whole class. A class is a large group of students, but, generally, there are no predefined common characteristics between its members. Similarly to GM, the class knowledge status is derived from the individual SM and is represented as an overlay upon the domain concepts. By using the CM, the advice generator can point to the teaching parts of the course that cause problems to the majority of the students, the most preferable types of learning objects visited by the students, communication activities used often or rarely, etc. (see Section 5).

4.4 Diagnosing an individual student's knowledge in TADV

The main source for extracting student, group, and class models in TADV is the tracking data collected by WCMS. This data usually includes the name of the accessed learning object and the time spent by a student working on that learning object (elapsed time). In TADV, elapsed time is used to rationalise the system's interpretations of the student's interactions with the provided learning objects, and to judge the changes in the student's understanding after reading the available learning objects.

The fuzzy approach used in TADV is a variant of the MYCIN model of reasoning in uncertain environments (Turban, 1993; Buchanan & Shortliffe, 1997) adapted to deal with individual and group models. TADV assigns a measure of belief (*MB*) or a measure of disbelief (*MD*) to every interaction a student makes with a learning object or an assessment quiz. Figure 3 shows the belief graph used to compute *MB* when a student interacts with a learning object *o* for a time *t*. TADV considers that the following attributes of *o*, which extend the IEEE LOM meta-data standard (see Section 3), are added to the objects in DMK (by a domain expert/teacher):

- *TMIN(o)* – minimum time required to consider that a student has visited the learning object *o* (this excludes situations when students browse through the material without reading it).
- *T1(o)* and *T2(o)* – optimal time interval for a student to familiarize with the learning object *o* (this takes into account that the students' reading pace may differ).
- *MB(o)* – measure of belief that a student may gain some understanding of *c* from the material in the learning object *o* when *t* is within the optimal time interval (this defines that a proper familiarisation with the course material increases the student's understanding of the concept presented in this material.
- *TMAX(o)* – maximum time for familiarizing with the learning object *o*, i.e. it is assumed that there is no more impact on a student's understanding if he/she stays on *o* longer than *TMAX(o)* (this accommodates situations when a page stays open without the student working on it).
- *MBMAX(o)* – teacher's belief about the understanding of *c* gained by a student who stays on *o* beyond the maximum time. The main justification for including *MBMAX(o)*, which corresponds to the belief at *TMAX(o)*, and is normally less than *MB(o)*, is that a student spends longer time working with a learning object: either due to problems he/she faced in understanding the concept or that he/she might have opened the page without working on it effectively.

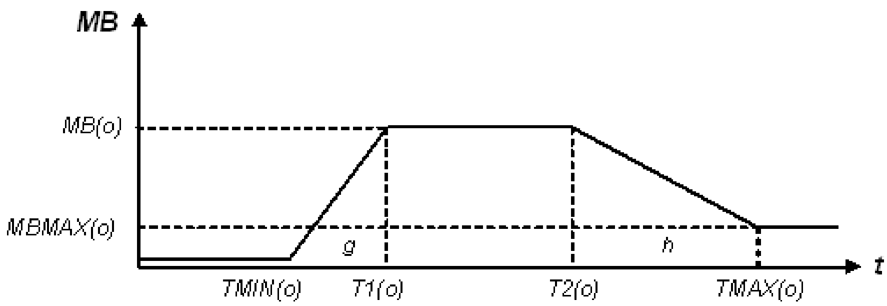

Figure 3: Belief graph representing the fuzzy membership function in TADV.

The membership function in TADV, shown in Figure 3, indicates that the assigned value of *MB* should be zero, if the student does not spend time greater than the defined minimum reading time (*t* < *TMIN(o)*). If *t* increases so that it is greater than *TMIN(o)* but is still less than *T1(o)*, then, depending on *t*, a partial value of the complete understanding measure of belief defined for this learning object, *MB(o)*, should be assigned to the interaction. This means that TADV assigns the measure of belief to the interaction linearly and as *t* increases. If the elapsed time has increased so that (*T1(o)* ≤ *t* ≤ *T2(o)*), then the complete measure of belief, *MB(o)*, will be assigned to the interaction. Upon the rise of the elapsed time so that it becomes greater than *T2(o)*, TADV should gradually start to decrease the assigned measure of belief until the reaching of *TMAX(o)*, at which TADV should assign the understanding measure of belief *MBMAX(o)*, for any time beyond *TMAX(o)*. Considering these criteria and the belief graph shown in Figure 4.8, the assigned measure of belief, *MB*, is calculated according to the equations (1), (2), (3), (4), and (5).

$$MB = 0 \quad \text{if } t < TMIN(o) \tag{1}$$

$$= MB(o)(t - TMIN(o))/g \quad \text{if } TMIN(o) \le t < T1(o) \tag{2}$$

$$= MB(o) \quad \text{if } T1(o) \le t \le T2(o) \tag{3}$$

$$= (MBMAX(o) - MB(o))(t - T2(o))/h + MB(o) \quad \text{if } T2(o) < t \le TMAX(o) \tag{4}$$

$$= MBMAX(o) \quad \text{if } t > TMAX(o) \tag{5}$$

where $g = T1(o) - TMIN(o)$ and $h = TMAX(o) - T2(o)$

When the student does not work on one of the main learning objects related to a domain concept *c*, and the time specified for studying the concept in the course calendar is passed, TADV applies the above membership function to calculate a measure of disbelief *MD(o)* that the student understands *c* based on evidence coming from the lack of interaction with *o*. In this case, *MD(o)* takes the value of *MB(o)*, calculated in equation (3), but considers this as negative evidence for the understanding of concept *c*.

To illustrate how the belief graph is applied, let us assume that a learning object ***o*** with an **example of ONE-TO-ONE FUNCTION** has the following meta-data:

TMIN(o)=2 (i.e. it would require minimum 2 minutes for a student to gain some understanding of o_1);

T1(o) = 5 and *T2(o)* = 10 min (i.e. the optimum time to understand o_1 is 5 to 10 minutes);

MB(o) = 0.2 (i.e. we believe that the student will slightly increase their knowledge if they read the example, for another object, with a detailed explanation of ONE-TO-ONE FUNCTION, the measure of belief may be higher, e.g. 0.4);

TMAX(o) = 15 (i.e. the maximum time to spend on *o* is 15minutes);

MBMAX(o)=0.1 (i.e. the teacher believes that the student's knowledge on the concept would increase very little if they stay longer than 15 min, i.e. they may be struggling or maybe doing something else and not reading the example)

The tracking data may include the following records for *o*[2]:

`Student S1 did not open o`. In this case, we do not have evidence, based on *o*, that the student's knowledge of ONE-TO-ONE FUNCTION has changed;

`Student S2 read o for 1 minute`. In this case, *MB*=0 from equation (1);

`Student S3 read o for 4 minutes.` In this case, we apply equation (2) and calculate that *MB*=0.13;

[2] Note that the format of the records has been simplified to make it easy to follow. The tracking data is usually given in a format specific for the particular WCMS (e.g. in a text file or a data base table).

`Student` S_4 `read` *`o`* `for 6 minutes`. In this case, *MB*=0.2, from equation (3);

`Student` S_5 `read` *`o`* `for 12 minutes`. In this case, we apply equation (4) and calculate that *MB* = 0.16;

`Student` S_6 `read` *`o`* `for 30 minutes`. In this case, *MB*=0.1, from equation (5).

Note that interactions with learning objects, including those that lie in the optimal time interval, do not give significant evidence that a student has understood a concept. Therefore, the values for measure of belief associated with learning objects are usually small. On the other hand, the performance at assessment quizzes can give a more reliable evidence for the student's understanding of a concept. Consequently, the values for measure of belief associated with assessment quizzes are usually higher. Through aggregation (combination) of small pieces of belief resulting from different interactions with learning objects and assessment quizzes related to a domain concept, TADV calculates the measure of belief for the understanding of this concept. The fuzzy membership function used is defined below.

It is important to mention that according to the criteria described, it is necessary to acquire seven metadata attributes from the domain expert for each learning object: *TMIN(o), T1(o), T2(o), TMAX(o), MB(o), MBMAX(o),* and *MD(o).* This may require additional effort from the course teachers and designers. It appears feasible to simplify the process by considering actions like:

- Defining a constant value for *TMIN(o)* for all learning objects.
- Defining a formula to compute *TMAX(o)* as a function of *T2(o)* for all learning objects (e.g. *TMAX(o)* = 2* *T2(o)*)
- Defining a formula to compute *MBMAX(o)* as a function of *MB(o)* for all learning objects (e.g. *MBMAX(o)* = 0.5* *MB(o)*)

To calculate the measures of belief and disbelief resulting from a student's interaction with an assessment quiz *q* related to a concept *c*, the following attributes of *q* (given by the domain expert/teacher and added to the meta-data in DMK) are taken into account:

- *MBC(q)* – measures the belief that the student understands *c* when his/her solution of *q* is correct.
- *MDW(q)* – measures the belief that the student does not understand *c* when his/her solution of *q* is wrong.
- *MDN(q)* - measures the belief that the student does not understand *c* when he/she has not produced a solution of *q* in the time interval specified by the course calendar.

For the interactions that reflect the student's communication activities, TADV does not assign any measures of belief or measures of disbelief. Instead, these interactions are used to update the Student Preferences Model, so that it is possible to know which type of communication activity the student prefers and to decide whether the student actively participates in discussions with peers. Note that every interaction with the course (not just the communication activities but also the interaction with learning objects and assessment quizzes) is taken into account in the update of the student's preference model. For example, if an interaction related to learning object (*o*) occurred, then this will lead to incrementing the number of student hits to the type of knowledge (text, presentation, simulation, etc.) indicated by the definition of *o* in DMK. A student's interaction with an assessment quiz (*q*) is used to increment the number of hits to the assessment quizzes in the student preferences model. In the same way, posting a message to a discussion forum is registered as a communication activity *d* and will increment the number of posts made by the student.

To illustrate the diagnosing mechanism used to assess the student's knowledge status on a specific concept *c*, let us consider a particular state of the course period within the course calendar. For every student, we will denote the current understanding measures of belief and disbelief of the concept *c* with $MB(c)_{curr}$ and $MD(c)_{curr}$, respectively. We will also assume that *MB* is the assigned measure of belief to one of the student's interactions stored in his/her Student Behaviour Model. Now, we will calculate the new measure of belief of *c* as follows:

$$MB(c)_{new} = MB(c)_{curr} + MB[1 - MB(c)_{curr}] \qquad (6)$$

$MB(c)_{new}$ will then become the current measure of belief of the concept *c* and can be used in the follow-up calculations. The action taken by equation (6) can be stated as: after reading or working on one of the learning objects related to the concept *c*, the concept understanding measure of belief is increased by some increment. This increment is computed by taking the difference between the complete (certain) belief, i.e. 1, and the current belief. *MB*, the assigned measure of belief of the new interaction, then scales this difference.

In the case where some understanding measure of disbelief is indicated by TADV (e.g. the student has not read or worked on one of the mandatory learning objects related to *c*) and *MD(o)* is its measure of disbelief, then it is possible to calculate the new measure of disbelief using equation (7).

$$MD(c)_{new} = MD(c)_{curr} + MD(o)[1 - MD(c)_{curr}] \qquad (7)$$

Equation (7) can be explained similarly to equation (6): if there is evidence that the student has not read or worked on the learning object (*o*), then the concept understanding measure of disbelief is increased by some increment. This increment is calculated by taking the difference between the complete (certain) disbelief, i.e. 1, and the current disbelief. This difference is then scaled by the disbelief in the new evidence.

The criteria used to manipulate interactions with learning objects can also be used to manipulate interactions with assessment quizzes related to concept *c*. Equations (8), (9), and (10) are applied in the cases when the student has solved the quiz correctly, wrongly, or has not solved the quiz, respectively.

$$MB(c)_{new} = MB(c)_{curr} + MBC(q)[1 - MB(c)_{curr}] \qquad (8)$$

$$MD(c)_{new} = MD(c)_{curr} + MDW(q)[1 - MD(c)_{curr}] \qquad (9)$$

$$MD(c)_{new} = MD(c)_{curr} + MDN(q)[1 - MD(c)_{curr}] \qquad (10)$$

At any instance during the evaluation process, the certainty factor associated with *c* to indicate the student's understanding of *c* is calculated by subtracting *MD(c)* from *MB(c)*:

$$CF(c) = MB(c) - MD(c) \qquad (11)$$

The initial values of *MB*, *MD*, and *CF* for each domain concept *c* are considered to be zero. For the subsequent calculations, TADV applies equations (6) – (11).

According to the value of *CF(c)*, TADV will assign the concept to one of the fuzzy sets defined to indicate the different mastering or understanding levels of the concepts. There are three fuzzy sets defined in TADV:

- *Completely Learned* (CL) set of concepts, which include the concepts that according to TADV are believed to have been completely mastered and understood by the student. No advice will be generated regarding improving the knowledge of those concepts; instead, TADV may advise the facilitator/teacher to motivate the student to help his/her peers who have problems with these concepts.
- *Learned* (L) set of concepts, which include the concepts TADV believes are understood by the student but not completely. Some advice may be generated to the teacher about

the mastering of these concepts, as well as some suggestions, if appropriate, to guide the student to enhance his/her level on these concepts.

- *Not Learned* (NL) set of concepts, which include the concepts TADV believes have not been understood by the student. Appropriate advice should be generated to the teacher informing that the student is struggling with these concepts, as well as suggesting possible actions to be taken by the teacher and/or the student to increase the student's understanding of these concepts.

In TADV, it is possible for the teachers or the facilitators to define the boundaries for each of these sets, for example one possible scheme is as follows:

$c \in$ *Completely Learned* set of concepts if $0.7 \le CF(c) \le 1.0$

$c \in$ *Learned* set of concepts if $0.4 \le CF(c) < 0.7$

$c \in$ *Not Learned* set of concepts if $-1.0 \le CF(c) < 0.4$

TADV can also evaluate the student in a comprehensive way by calculating his/her general evaluation in all studied concepts (determination of candidate concepts is guided by the course calendar) as a function of the certainty factors of the individual concepts. The approach of weighted average is used to compute the average certainty factor for a student *S*, using the certainty factors of all domain concepts. The average certainty factor for each student is used to assign him/her to one of the fuzzy student sets defined to categorize students according to their knowledge status: Excellent, Good, or Weak. TADV gives the course facilitator the possibility to define the boundaries for each category.

4.5 Diagnosing the knowledge of groups and classes

For every domain concept, TADV considers measure of belief *GMB(c)* that the group understands *c*. *GMB(c)* is calculated by the aggregation of the measures of beliefs for understanding *c* of all individual students belonging to the group, i.e.

$$GMB(c)_{new} = GMB(c)_{curr} + MB(c)_k[1 - GMB(c)_{curr}] \quad \text{when } k = 1, 2, \ldots, n \qquad (13)$$

where *n* is the number of students in the group. In the first use of (13), the initial value of $GMB(c)_{curr}$ will be zero.

To illustrate, we will consider *c* = ONE-TO-ON FUNCTION. Assume that a group *G* includes students S_1, S_2, S_3, S_4, S_5, S_6, for whom we calculated the measure of belief for concept ONE-TO-ON FUNCTION in the example in Section 4.4. We will use these values to calculate the group measure of belief (note that, in order to make the example easier to follow, we consider the evidence about the students' knowledge of ONE-TO-ON FUNCTION to be based only on their interaction with learning object *o*, in reality, there will be many interactions that will be used to calculated MB for each student by applying equation (8)).

Initially, $GMB(c)_{curr}$=0. From S_1, we do not have changes to GMB, as S_1 has not interacted with the learning objects about ONE-TO-ON FUNCTION.

For student S_2, we calculated MB(ONE-TO-ON FUNCTION)$_2$=0, i.e. S_2 will not bring changes to the group measure of belief about ONE-TO-ON FUNCTION.

For student S_3, we calculated MB(ONE-TO-ON FUNCTION)$_3$=0.13. Thus,

*GMB(*ONE-TO-ON FUNCTION)$_{new}$=0+0.13=0.13

For student S_4, we calculated MB(ONE-TO-ON FUNCTION)$_4$=0.2. Thus,

*GMB(*ONE-TO-ON FUNCTION)$_{new}$=0.13+0.2(1-0.13)=0.304

For student S_5, we calculated MB(ONE-TO-ON FUNCTION)$_5$=0.16. Thus,

$GMB($ONE-TO-ON FUNCTION$)_{new}$=0.304+0.16(1-0.304)=0.415[3]

For student S_6, we calculated MB(ONE-TO-ON FUNCTION)$_6$=0.1. Thus,

$GMB($ONE-TO-ON FUNCTION$)_{new}$=0.415+0.1(1-0.415)=0.474

Therefore, for $G=\{S_1, S_2, S_3, S_4, S_5, S_6\}$, GMB(ONE-TO-ON FUNCTION)= 0.474.

In a similar way, the group's concept understanding measure of disbelief, *GMD(c)*, is calculated by the aggregation of individual student's concepts measures of disbelief as shown in equation (14).

$$GMD(c)_{new} = GMD(c)_{curr} + MD(c)_k[1 - GMD(c)_{curr}] \quad \text{when } k = 1, 2, \ldots, n \qquad (14)$$

The group's concept understanding certainty factor *GCF(c)*, can be calculated using (15). The general evaluation of a group of students, *GEVAL(G)*, can be calculated by taking the average of the students' *AVGCF*. Equation (16) can be used to compute the general evaluation of a group *G* of n students ($S_1, S_2, \ldots, Sn$).

$$GCF(c) = GMB(c) - GMD(c) \qquad (15)$$

$$GEVAL(G) = [\sum_{i=1}^{n} AVGCF(S_i)]/n \qquad (16)$$

GEVAL(G) can then be used to assign the group to one of the fuzzy categories defined to differentiate between groups of students. A similar approach to one used to categorize students is also used to categorize groups.

Similarly, we can calculate the measure of belief of the class' understanding of a concept *c*, *CMB(c)*, by the aggregation of the individual students' measures of belief of *c*, i.e

$$CMB(c)_{new} = CMB(c)_{curr} + MB(c)_k[1 - CMB(c)_{curr}] \quad \text{when } k = 1, 2, \ldots, m \qquad (17)$$

where *m* is the number of students in the class. In the first use of equation (17), the initial value of $CMB(c)_{curr}$ is zero. In the same way, it is possible to calculate the class concept understanding measures of disbelief, *CMD(c)* by the aggregation of individual student's concepts measures of disbelief as shown in equation (18). It is possible to calculate the class concept understanding certainty factor *CCF(c)*, using equation (19). *CEVAL(C)*, the general evaluation of the class with m students ($S_1, S_2, \ldots, Sm$) can be calculated by taking the average of the students' *AVGCF*, equation (20).

$$CMD(c)_{new} = CMD(c)_{curr} + MD(c)_k[1 - CMD(c)_{curr}] \quad \text{for } k = 1, 2, .., m \qquad (18)$$

$$CCF(c) = CMB(c) - CMD(c) \qquad (19)$$

$$CEVAL(C) = [\sum_{i=1}^{m} AVGCF(S_i)]/m \qquad (20)$$

Knowing the knowledge status of a group or a class, TADV can identify, *struggling students* (whose knowledge status is weak), and *advanced students* (whose knowledge status is excellent), with respect to the group or class. For example, for $G=\{S_1, S_2, S_3, S_4, S_5, S_6\}$, students S_4 and S_5 appear most knowledgeable about ONE-TO-ON FUNCTION, while S_1 and S_2 have not provided evidence that they know ONE-TO-ON FUNCTION. This information will be used by the Advice Generator when deciding what actions would be appropriate for the students in *G*.

[3] Note that the values are rounded to the third decimal digit.

In addition to the knowledge status of a group or the class, TADV also considers general interaction characteristics of the group or class, based on the individual students' behaviour models. Therefore, it is possible to know: *delayed students* (who delay with the course calendar), *communicative members* (who often post messages in the discussion forums) and *passive readers* (who read course material but do not interact with others in discussion forums). These cases are considered by the advice generator when suggesting activities related to a group or the whole class, as discussed next.

The reliability of the TADV student modelling mechanisms proposed in this research affect the dependency of these mechanisms onto the values of metadata attributes either required to describe the standard characteristics of the learning objects (IEEE LOM), or attributes and parameters used to run the fuzzy student modelling mechanism (e.g. measures of beliefs and disbeliefs, boundaries used to evaluate concepts-learning status, and boundaries used to generally evaluate students and their communicative status). Consequently, the mechanism adopted in this research is strongly dependent on the initial data supplied by the teachers. People usually tend to minimize their efforts supplying metadata, which in turn may lead to incomplete and inconsistent metadata (Pinkwart et al., 2004). On the other hand, the assigned values of metadata attributes are usually subjective, and present the view of a particular teacher about the course material that he/she has developed. These problems are common in all projects which need to deal with metadata and a general solution seems out of reach. However, some solutions are being proposed, e.g. Pinkwart et al. (2004) describes an approach for partial automatic generation of metadata in a collaborative modelling environment to reduce the user's effort required to prepare metadata. In our case, the problem of the subjectivity of some metadata attributes (e.g. typical reading times for learning objects) and fuzzy parameters (e.g. learning status boundaries) can be solved by acquiring this data from several domain experts which may lead to more reasonable values. This, in turn, may increase the effort and time required to collect metadata. Sensitivity analysis methods may be used, depending on the availability of resultant data from several system runs, to fine-tune the values of some metadata attributes and fuzzy parameters. This, however, may require long-term studies in real distance learning environments.

5. Advice Generator

A critical component in TADV is the Advice Generator (AG), which is the kernel of the proposed framework. Based on the knowledge status and interaction characteristics of individual students, groups and classes, AG generates appropriate advice to the course facilitators, including suggestions for posting messages to individuals or groups or encouraging group interactions and peer help.

TADV adopts heuristics that indicate what advice or help will be appropriate in certain situations. A set of predefined conditions is used to identify advising situations. Advice templates[4] are associated with the situations. When AG recognizes a situation (based on student SM, GM, and CM), the corresponding template is activated to generate advice to the teacher, together with recommendation of what can be sent to the student. In some cases, TADV may just produce a statement that describes a situation without suggesting what the teacher should do to remedy the problem. This can happen when TADV is either unable to identify reasons for the problem, or highlights the problem and lets the facilitator decide what pedagogical actions are needed based on his/her experience.

[4] Templates provide a fairly robust way of generating pieces of advice without using sophisticated natural language generation techniques which are outside the scope of this work.

TADV is designed so that it is possible to deliver several types of advice, organized in advice taxonomy, as described next.

5.1 Advice Types in TADV

TADV follows an advice taxonomy based on our analysis of problems with distance courses, as discussed in the literature, the observation of several online sessions between facilitators, and distance students in some web based courses and confirmed in interviews with several Web-based course teachers (Kosba, 2005). Three advice categories are considered:

- Advice concerning *individual students* (*Type-1*): includes several subtypes, such as advice related to a student's knowledge status, students who have unsatisfactory learning levels, uncommunicative students, students who have not started working on or are delaying with the course, etc;
- Advice concerning *groups* (*Type-2*): provides information about common problems that face a group of students and includes advice related to the knowledge states of groups, groups with satisfactory/unsatisfactory learning levels, uncommunicative groups, etc;
- Advice concerning the *whole class* (*Type-3*): provides information about the status and behaviour of the whole class and includes advice related to the class knowledge status, excellent and weak students relative to the whole class, most and least communicative students, etc.

Type-1: Advice related to individual students

Type-1 advice is used to inform a course facilitator about problems that individual students may face and to suggest possible actions to remedy the problems, depending on reasons that may have led to the problems, as indicated from the student's interactions. This type of advice is divided into several subtypes, as described below.

Type 1-1 advice informs about problems related to the student's knowledge status. As described in Section 4, TADV measures the student's knowledge status regarding each domain concept as "Completely Learned", "Learned", or "Not Learned". Type 1-1 advice is generated when the student's knowledge model includes concepts with "Not Learned" or "Learned" status. In this case, AG investigates the reason(s) that led to this problem, which may include:

- The student has not completely read and worked on the learning objects and assessment quizzes related to the concept;
- The student has not completely mastered the related prerequisite concepts;
- The student has not participated in the communication activities related to the concept;

To specifically investigate the possible reason(s), AG performs analysis using the information available in the student behaviour model and the student knowledge model.

Type 1-2 advice informs about the student's progress with the course material related to a certain concept. The AG uses the course calendar (which is part of DMK) and the student behaviour model (which is part of the student model) to determine if the student is delayed with (lagging behind) the course-studying plan. The AG will deliver advice to the facilitator with information such as the student name, the concepts with which student is delayed, and the delay time (time-lag) of each concept. The facilitator may send this information to the student or take the necessary actions, depending on the delay times and student case.

Type 1-3 advice offers more attention to the students who are at unsatisfactory learning levels. It focuses on students evaluated as “Weak” (see Section 4.2). TADV will classify those “Weak” students according to their communication levels (Weak and uncommunicative, Weak and normally communicative, Weak and highly communicative). Actions suggested to the facilitator can include: encouraging the students to contact more knowledgeable peers who are communicative, creating special online chat sessions with groups of weak students, or communicating directly with each individual student.

Type 1-4 informs the facilitator about students with advanced learning levels, i.e. evaluated as “Excellent” (note the comparison with Type 1-3). As in Type 1-3 advice, TADV will combine the knowledge status with the student’s communication activities. The facilitator will be advised to praise the students for their learning levels and to direct them to help other “Weak” peers by talking to them through e-mails or discussion forums. Special attention can be given to the students who are excellent but uncommunicative. The teacher can explain to them the advantages of discussing with others and can encourage them to take a more active role in the discussion forums.

Type 1-5 informs the facilitator about students who had not started working with the course until the time of advice generation session. If this type of advice is generated for one of the students, then other Type-1 advice will be suppressed to filter redundant information.

Type-2: Advice related to groups of students

Type-2 advice is concerned with a group of students. The learning level of each concept and the general learning level of a set of concepts will be monitored to identify problematic situations concerning the group’s learning. Note that the situations are based on the group knowledge status, calculated as a function of the knowledge status of each individual student in the group, as discussed in Section 4.5. Type-2 advice enables the facilitators to know about common problems that face a group and to correlate these problems to group characteristics. The facilitator can provide the students with appropriate feedback and guiding information to address the highlighted problems. The following advice subtypes are considered.

Type 2-1 informs the facilitator about problems related to the group’s knowledge status. This advice subtype will be generated when the group knowledge model shows concepts with “Not Learned” or “Learned” levels. Similar to the actions performed in Type 1-1 advice, AG searches for reason(s) that may lead to this situation and presents this information to the facilitator together with a recommendation of some actions that may be taken, including encouraging students to pay attention at particular concepts or forming group activities involving advanced and struggling students.

Type 2-2 informs the facilitators about problematic situations related to the groups' learning levels. The facilitator’s attention is directed to groups, which have unsatisfactory learning levels. Type 2-2 advice that concerns groups is similar to Type 1-3 advice that concerns individual students. Advice Type 2-2 is used to highlight to the facilitator the “Weak” groups. TADV will classify those “Weak” groups according to their communication levels (weak and uncommunicative, weak and normally communicative, and weak and highly communicative). The facilitator can take some actions, such as talking directly to the group members, creating a special discussion forum or chat sessions for the group, or asking “Excellent” students from the group to help their peers.

Type 2-3 informs the facilitator about groups with satisfactory learning levels. In this case, AG looks for the “Excellent” groups. As in Type 2-2 advice, TADV will classify “Excellent” groups according to their knowledge status and will combine it with the communication levels. This information will be highlighted to the facilitator who may decide to encourage students in these groups to maintain their general learning levels and/or to give help to “Weak” groups via e-mail, chat, or by posting on the discussion forums.

Type 2-4 informs the facilitator that most (e.g. more than 50%) students in the group have not started working with the course up to the time of advice generation session. In this case, other Type-2 advice will not be generated because it is expected that most of the group concepts' learning level are "Not Learned".

Type-3: Advice related to the whole class

Type-3 advice is concerned with the status and behaviour of the whole class. Advice of this type does not automatically result in subsequent recommended advice or feedback to individual students. Instead, it is primarily used to aid course facilitators in managing their distance classes. This type of advice is important to the facilitator because it gives an overview of the class, and highlights the common problems. The facilitator may try to solve these problems during the course period by taking appropriate educational actions. Furthermore, analysing the generated information and the reasons behind common class problems, the facilitator may consider how to avoid the occurrence of these problems in the subsequent courses.

Type 3-1 informs the facilitator about problems related to the knowledge status of the whole class. This advice will be generated when the AG detects concepts with "Not Learned" or "Learned" levels in the class knowledge model. The AG will search for possible reason(s) that might have led to this situation and will notify the facilitator about this. According to the situation, the facilitator may take appropriate decisions and pass them to all students in the class. For example, if the class knowledge model indicates that a concept *c* is "Not Learned" by the class because most students have not studied the learning objects related to *c*, TADV will highlight this situation to the facilitator. In this case, the facilitator may encourage the students to start studying learning objects related to *c*. On the other hand, if the students have read the learning objects about a concept and are still struggling with that concept, the teacher may find it helpful to provide some additional learning objects or to start a discussion forum to clarify issues that may have missed by the students.

Type 3-2 advice is generated to inform the facilitator about excellent students (for example, the top three) and weak students (for example, the bottom three) relative to the whole class during each of the advice generating sessions. The former may be assigned roles in managing discussion forums or helping struggling students. The latter may be potential drop-outs for whom the facilitator’s special attention and tailored help can be crucial.

Type 3-3 informs the facilitator about the most and least communicative students relative to the whole class during each of the advice generating sessions. The former can be praised, especially if their knowledge status is also high, while the latter should be encouraged to participate in discussion forums and may be assigned tasks that require group work.

Type 3-4 informs the facilitator about the most and least active students relative to the whole class during each of the advice generating sessions. Students’ activity is measured by the aggregate number of interactions (hits) made by the student in different sessions. Information from this advice can be compared to information from advice Type 3-2 to correlate between the students’ activity and their general learning levels.

Type 3-5 informs the facilitator that most (e.g. more than 50%) students in the class have not started working with the course up to the time of advice generation session. In this case, other Type-3 advice concerned with class learning and communication levels will not be generated to avoid overloading the facilitator with redundant information.

Finally, it should be noted that it is possible to add new advice to the subtypes considered for individual students, groups, and classes. In this case, reasons that determine the need for the advice have to be defined based on the conditions in the student, group, or class models.

5.2 Advice Generating Criteria

AG is based on recognizing situations when the teacher may be offered some advice. Each situation is defined by including the following:

- ***Stimulating Evidence (E):*** the situation that motivates AG to generate the advice, defined as $E(e_1, e_2, e_3)$ where e_1 is the name of the student, group, or class that cause the stimulating evidence, e_2 is the name of a domain concept, and e_3 is the status (CL, L, NL, or delayed) of the domain concept carried by e_2. For instance, $E(S_1, c_b, NL)$ means that for student S_1, concept c_b is "Not learned". If e_2 is not specified then e_3 is considered as the status of the student. For example $E(S_1, Weak)$ means that knowledge status of S_1 is evaluated by TADV as “Weak”;
- ***Investigated Reason (R):*** according to the discovered E, the AG will check SM, GM, and CM to find reasons that may have caused this evidence. The investigated reason is generally formalized as $R(r_1, r_2, r_3)$ where r_1 is the name of the domain concept related to e_2 with r_2 concept type of relation (Strong/Moderate/Weak) and r_3 is the status of r_1. For example, if $R(c_a, Strong, NL)$ is the investigated reason of $E(S_1, c_b, NL)$ then AG can reason that the "not learned" status of c_a (that is strongly related to c_b) is the reason for this E. More examples are given in Table I;
- ***Advice from TADV to facilitator (A):*** depending on the investigated reason R, the AG will deliver the appropriate piece of advice A to the facilitator. A is defined as $A(P_1,\ldots, P_n)$ where $P_1,\ldots, P_n$ are the parameters carried with the advice template associated with R. There are four basic parameter types used in advice templates: concept name, student name, group name, and class name, see Table I for examples;
- ***Recommended actions that the facilitator can undertake (T):*** If possible, depending on R, AG will produce a predefined advice template that recommends messages the facilitator may send to a student, a group, or the whole class, or suggests other possible actions (e.g. group activities for weak students). This item does not exist when the AG is unable to find reasons that might have led to the current stimulating evidence or when the advice is concerned merely with highlighting important information to the facilitator. The recommendation is generally formalized as $T(P_1,\ldots, P_k)$ where $P_1,\ldots, P_k$ are parameters carried with the template. Table I shows some templates with recommendations;
- ***Next AG Action:*** For some stimulating evidence there is a possibility of having many reasons. When a reason is investigated, AG will proceed with the reason and generate the appropriate advice. At this point, depending on the investigated reason, AG will either end the processing of the current evidence, or keep searching for other reasons. When a reason is considered to be sufficient, then its “Next AG Action” is specified as "*Look for new stimulating evidence*", to notify AG to *end* processing of the current evidence. When a reason is considered to be insufficient, its “Next AG Action” is specified as "*Look for other reasons*", i.e. AG has to continue processing of E by searching for other candidate reasons.

Table I. Examples of defining situations for generating advice to individual students (Type-1), groups of students (Type-2) and the whole class (Type-3). Note that the parameters indicating concepts and students will are filled in by AG with the appropriate values from SM, GM, CM, and DMK. For this example, we consider students from the illustrations given in sections 4.4 and 4.5.

Investigated Reason (*R*)	**Advice from TADV to facilitator (*A*)**	**Recommended advice from facilitator to the student (*T*)**	**Next AG Action**
Type-1 Student advice [concerning stimulating evidence *E*(S_1, INVERSE ONE-TO-ONE FUNCTION, *NL*)]			
*(*ONE-TO-ONE FUNCTION*, Strong, NL)*	Student S_1 should be advised to study ONE-TO-ONE FUNCTION.	In order for you to master INVERSE ONE-TO-ONE FUNCTION, it is highly recommended that you study ONE-TO-ONE FUNCTION first.	Look for new evidence
S_5 is diagnosed as uncommunicative with regard to INVERSE ONE-TO-ONE FUNCTION	Student S_5 should be encouraged to participate effectively in the communication activities related to INVERSE ONE-TO-ONE FUNCTION[5]. Students {S_3, S_4} are communicative and have already mastered INVERSE ONE-TO-ONE FUNCTION	You have not participated effectively in the discussion forum about INVERSE ONE-TO-ONE FUNCTION. It may be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact S_3 or S_4 to discuss INVERSE ONE-TO-ONE FUNCTION.	Look for new evidence
Type-2 Group advice [concerning stimulating evidence *E*(*G*, INVERSE ONE-TO-ONE FUNCTION, *UL*)]			
*(*ONE-TO-ONE FUNCTION*, Strong, NL)*	*G* members should be advised to work more with concept ONE-TO-ONE FUNCTION. It may be helpful to highlight the link between ONE-TO-ONE FUNCTION and INVERSE ONE-TO-ONE FUNCTION in a discussion forum. Students {S_3, S_4}, belonging to *G*, have already mastered INVERSE ONE-TO-ONE FUNCTION and are communicative.	INVERSE ONE-TO-ONE FUNCTION appears to be a common problem for group *G*. You need to work more on ONE-TO-ONE FUNCTION which is required for the understanding of INVERSE ONE-TO-ONE FUNCTION. Students S_3 and S_4 may be able to provide help.	Look for new evidence
G is indicated as uncommunicative with regard to INVERSE ONE-TO-ONE FUNCTION	INVERSE ONE-TO-ONE FUNCTION appears to be a common problem for students in *G*. TADV notes that most *G* members have not participated in the discussion forum about INVERSE ONE-TO-ONE FUNCTION. The *G* members should be encouraged to participate in communication activities related to INVERSE ONE-TO-ONE FUNCTION.	INVERSE ONE-TO-ONE FUNCTION appears to be a common problem for group *G*. Try to participate effectively in the discussion forum about INVERSE ONE-TO-ONE FUNCTION. You can post your questions there.	Look for new evidence
Type-3 Class advice [concerning stimulating evidence *E*(*C*, INVERSE ONE-TO-ONE FUNCTION, *NL*)]			
Course material about INVERSE ONE-TO-ONE FUNCTION *has been visited by most students*	INVERSE ONE-TO-ONE FUNCTION appears to be a common problem for the class. Most students have read the learning objects and have attempted the assessment quizzes about INVERSE ONE-TO-ONE FUNCTION.	Suggested actions for the facilitator: check the course material about INVERSE ONE-TO-ONE FUNCTION and/or initiate clarification discussions, if necessary.	Look for new evidence
C is indicated as uncommunicative with regard to INVERSE ONE-TO-ONE FUNCTION	INVERSE ONE-TO-ONE FUNCTION appears to be a common problem for students in *C*. TADV notes that class members are not participating in the discussion forum about INVERSE ONE-TO-ONE FUNCTION. *C* members should be encouraged to participate in communication activities related to INVERSE ONE-TO-ONE FUNCTION.	INVERSE ONE-TO-ONE FUNCTION appears to be a common problem for the whole class. Try to participate effectively in the discussion forum about INVERSE ONE-TO-ONE FUNCTION. You can post your questions there.	Look for new evidence

Figure 4 shows the main processes performed during advice generation, which include:

- ***Process 1: Look for stimulating evidence:*** uses inputs mainly from SM, GM, or CM, to locate the concepts with problematic learning status (i.e. not learned and learned concepts), and to indicate communicative characteristics of individual students, groups

[5] Note that TADV will advice the student to communicate about a concept only when the student is struggling with the concept.

of students or the whole class. It also uses the course calendar to find whether the students are delayed. The output of this process is the stimulating evidence *E*;

- ***Process 2: Find possible reason:*** uses *E* (the result from Process 1), the domain knowledge model (concept map, see Section 3), and SM, GM, or CM to investigate the reason behind *E*. The output of this process is the investigated reason *R*;
- ***Process 3: Find template, assign parameters, and generate advice:*** According to the reason *R* found by Process 2, an appropriate advice template is allocated and values for its parameters are assigned.

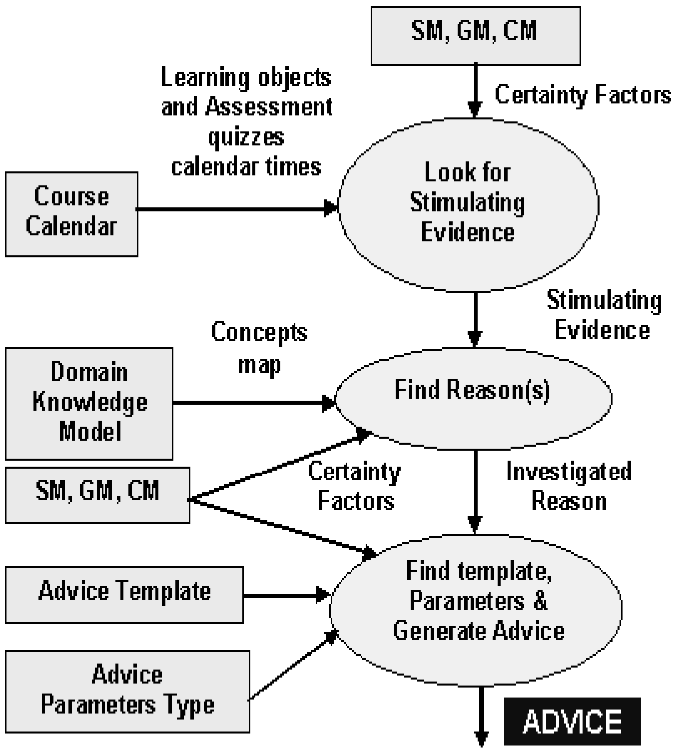

Figure 4. Processes performed during advice generation in TADV.

To sum up, the issues related to advice generation - advice types, advice selection, advice formulation, and advice generation criteria - have been described. The TADV advice generation mechanism is general, i.e. it is not dependent on a specific domain or on a specific WCMS. To validate the TADV framework, we have developed a demonstrator prototype integrated in an example distance learning course delivered with a specific WCMS.

6. TADV Prototype

The TADV design is based on an extensive study of information provided by WCMS, including practical experience with several platforms (Kosba, 2005). One of them, the Centra Knowledge Server, has been employed to demonstrate TADV in a Discrete Mathematics distance learning course at the Arab Academy for Science and Technology (AAST), Alexandria, Egypt. The Centra Knowledge Center has been extended, following the TADV architecture presented in Figure 1. SMB was constructed to extract student models from student tracking data, as outlined in Section 4; and AG was implemented to highlight problems of individuals, groups, and the whole class, as described in Section 5. This Section gives a detailed description of the TADV prototype.

6.1. Centra Knowledge Center

The Centra Knowledge Server is a flexible repository that can be used by educational organisations to tag and index their learning objects. It facilitates the capture, storage, delivery, and centralized management of knowledge. The browser-based Centra Knowledge Center allows users to view personalized, assigned learning topics and access, as well as search, a catalogue of available learning resources. Together, the Centra Server and the Centra Center offer powerful features to the users e.g. personalized learning, easy learning object creation, support for industry standards, and easy to use interface. The word "Centra" is used hereafter to denote both the Centra Knowledge Server and the Centra Knowledge Centre. Centra provides student tracking features which record detailed information about all types of interactions that students make with the available learning objects, assessment items, and communication and collaboration tools.

Centra uses Microsoft SQL2000 Server as a backend database management system. Therefore, it was necessary to know about its relational database model: where tracking information is stored, how tracking information can be interpreted against the used course materials and the students involved, etc. Most of the tracking information required to build the proposed student models (discussed in Section 4) is generated by Centra.

6.2 Implementation tools

The TADV prototype was implemented in Microsoft SQL2000 Server and Active Server Pages (ASP) technology with ODBC (Open Data Base Connectivity) drivers. The Web server was Microsoft Internet Information Server (MS-IIS) under a Microsoft Windows 2000 Server. Microsoft Visual Interdev V6.0 was used as a development tool and Visual Basic and Java scripts were used as development languages. The Domain Meta-Knowledge base, student, group and class models, in addition to the advice generation model, are stored as relational databases on the MS SQL Server. It contains tables to store metadata for all learning objects and assessment quizzes, relationships between domain concepts, course calendars, students' profiles, the models constructed to assess the knowledge of students, groups and classes, and all information related to the process of advice generation. The prototype was implemented as an extension of Centra and followed the architecture described in Section 2.

6.3 Domain and course preparation

A Discrete Mathematics course was selected for demonstrating the TADV prototype. The availability of the domain expert who volunteered to help in the process of course preparation and its metadata, and the possibility to teach part of this course in a distance manner, were the key reasons behind selecting this domain.

- Following the guidelines for structuring the course described in Section 3, the course was divided into two lessons: functions (Lesson-1) and relations (Lesson-2). Each lesson was then divided into a set of concepts (17 concepts for each lesson). The concept maps (described in Section 3) were then prepared for each of the specified lessons. Then, the difficulty levels and weights assigned to each of the course concepts were determined. Preparing learning objects related to each of the course concepts was one of the major tasks. The domain expert provided the text and examples necessary, from his point of view, for building the required knowledge of the selected lessons. The learning objects of each concept were then created using these materials. There are two main groups of learning objects related to each concept: a group which contains the text required to explain the concept, and a group which contains examples necessary to demonstrate the concept. 70 different learning objects were prepared for the TADV prototype.

The necessary quizzes were also prepared by the domain expert in a multiple-choice and true/false format. The domain expert provided us with the concepts related to each quiz, along with its correct answer. The total number of quizzes prepared for the prototype was 49.

The acquisition of the metadata required for describing learning objects and assessment quizzes was the last step in the course preparation phase. All prepared learning objects and assessments were returned back to the domain expert to decide the values of the required attributes necessary for the proposed fuzzy approach. The TADV belief graph (discussed in Section 4.4) was explained to the expert so that he could easily use it during this task.

6.4 Implementation of the TADV models and their integration in Centra

This section presents the tasks carried out, in order to implement the required TADV models as an extension of selected WCMS – Centra. This section shows that it is possible to apply the TADV framework within conventional WCMS that keep logs of tracking data.

As explained, the TADV architecture has three main data models that should be implemented – a model for Domain Meta Knowledge base, a model for student modelling features (individual student, group, and class models), and a model for advice generation features. In addition to these models, there is a model for the Domain Knowledge Base, which already exists through using Centra.

The proposed course structure was applied to the Centra content manager. Centra uses different terminology for courseware structuring (e.g. learning goals, learning objectives, etc.). Understanding what this terminology means and how it is related was very important to know how to create the course in a similar way to the proposed course structure. According to the definitions of the Centra learning resources, and with reference to the proposed course structure (discussed in Section 3), we used “learning goal” to represent “course”, “learning objective” to represent “lesson”, and “learning track” to represent “concept”. Learning objects related to a concept were assigned to one track. This showed the applicability and generality of the proposed course structure.

Centra uses SCORM standards to describe learning objects. SCORM combines standards from IEEE and IMS. Therefore, some of the metadata attributes proposed for Domain Meta Knowledge are already kept by Centra. The attributes required for fuzzy calculations (e.g. measures of belief and disbelief) are not represented by Centra and have been added for the purpose of TADV, as described in the next section.

Centra keeps student tracking data in a database format, which facilitates the process of a direct access to this data. Knowing the relational database model of Centra and the meanings of different attributes, codes, and keys was necessary for this prototype. Centra also keeps profiles of the registered students. Part of the data proposed for the Student Profile Model is already available in the profiles maintained by Centra.

The prototype implemented and integrated the following TADV components within CENTRA:

- Authoring tool to add the metadata attributes required by TADV and not represented by Centra;
- A component for student, group, and class modelling.
- Advice generation component.

In this implementation of TADV, the Student Model Builder was developed to read information about students' interactions directly from the Centra database and to calculate student, group and class models according to the mechanisms explained in Section 4. The module was developed so that it was possible to be automatically executed (in a batch mode) daily at a pre-scheduled time.

The Advice Generator was developed to generate the proposed advice according to the criteria explained in Section 5. The module was designed to use the most recent models constructed by SMB to generate the advice. AG could be executed from the facilitator interface at the facilitator's request at the time he/she needed to generate the advice.

Figure 5 illustrates how the TADV architecture (discussed in Section 2) was implemented as an extension of the course management system Centra. The main system's components and information flow between the components are shown, as well as the tools used for implementing the prototype.

6.5 The facilitator's and student's interfaces

One of the design objectives considered during the implementation of TADV was to fully integrate features of TADV and Centra, so that users (facilitators and students) would not feel that there were two different systems. Therefore, it was important to determine the functions that should be included in the facilitator and student main menus. This section presents the interfaces designed for the facilitators and the students.

6.5.1 Facilitator's main menu

There are six options in the facilitator's main menu:

System parameters option: allows the facilitator to set the parameters required for the student modelling mechanisms. Some of these parameters are included to simplify the process of metadata acquisition and entry. These values should be entered before entering the values of metadata attributes specified for learning objects and before starting the course. The parameters include the following attributes:

- TMIN parameter: if a value is entered to this parameter, then TMIN (the minimum time required for familiarizing with a learning object) for all learning objects will take the same value. Otherwise, a TMIN value should be acquired from the domain expert and entered for each learning object;
- TMAX parameter: Like TMIN, this parameter, if used, automatically calculates the values of TMAX (maximum familiarizing time) for all the learning objects as a percentage of T2 (the upper limit of the optimal time interval). The value for this parameter should be greater than 100. For example, if TMAX is set to be 150% of T2, then for a learning object with T2 = 10 minutes, TMAX will be 15 minutes;
- MBMAX parameter: This parameter, if used, automatically calculates the values of MBMAX (understanding measure of belief at the maximum familiarizing time) for all learning objects as a percentage of the MB (learning object measure of belief). The value of this parameter should be less than 100 because MBMAX is always less than MB;
- CL/L and L/UL boundaries: These mandatory parameters are used to determine the certainty factor boundaries, which are used to evaluate the concepts' learning status - Completely Learned (CL), Learned (L), and Not Learned (NL);

- Excellent/Good and Good/Weak boundaries: These mandatory parameters are used to determine the average certainty factor boundaries used to generally evaluate students regarding a group of concepts .

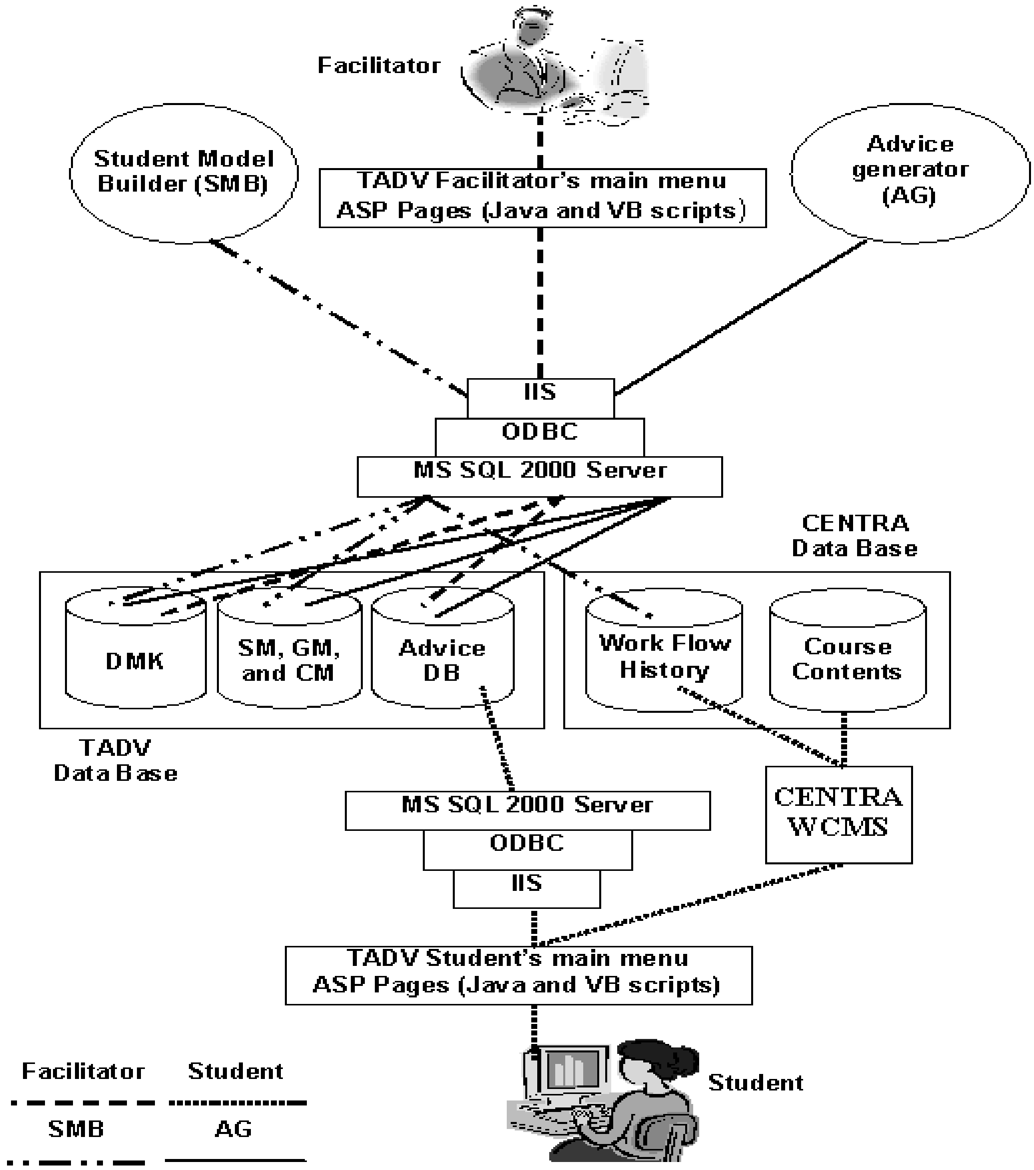

Figure 5. The Architecture of the TADV prototype: main components and implementation tools.

Selection of advice types option: allows the facilitator to select the types and the subtypes of the advice he/she likes to be generated by TADV. To be able to evaluate our proposed advice taxonomy, all advice types were selected for generation in this TADV implementation;

Creating course and entering values of metadata attributes: The option named "Metadata" allows the facilitator (or any one on their behalf) to enter the values of the required metadata attributes to the DMK. Due to the integration we have made with CENTRA, it was first necessary to create the course using CENTRA authoring tools, then use the "Metadata" option to enter the values of metadata attributes according to the parts of the created course. The option is designed such that it reads and displays the metadata of course parts already defined in the CENTRA database, and allows the facilitator to complete entry of the metadata required for TADV;

Managing students, groups, and classes: The option tagged "Management of Students, Groups, Class", allows entry of information related to Student Profile Models. It is also used to define groups and classes of students and facilitates assigning students to the defined groups and classes;

Generating advice: The option "Generate Advice" is used to start the process of advice generation. AG will generate only the types of advice selected by the facilitator using "Select Advice Type" option. The generated advice will be stored in the database prepared for this purpose along with the date of generation. TADV keeps all advice generated on different dates;

Viewing and sending advice: The "View Advice" option allows the facilitator to see the advice generated by the TADV. The facilitator can display the generated advice according to its main type (individual students, groups, or classes) and according to the selected student, group, or class. The facilitator can also review the recommended feedback proposed by TADV for students, and, if needed, modify it or freely compose the appropriate feedback according to the knowledge he/she grasped from TADV generated advice. In addition, the facilitator can select to send this feedback to the student or discard it. One of the important features offered by TADV is the possibility to open (display) the Student Knowledge Model to the facilitator. This feature gives the facilitator an overview of the status of student knowledge in one screen. It can further be used to examine the link between the generated advice and what is currently in the student knowledge model. Figure 6 shows a screen used to display advice to the facilitator.

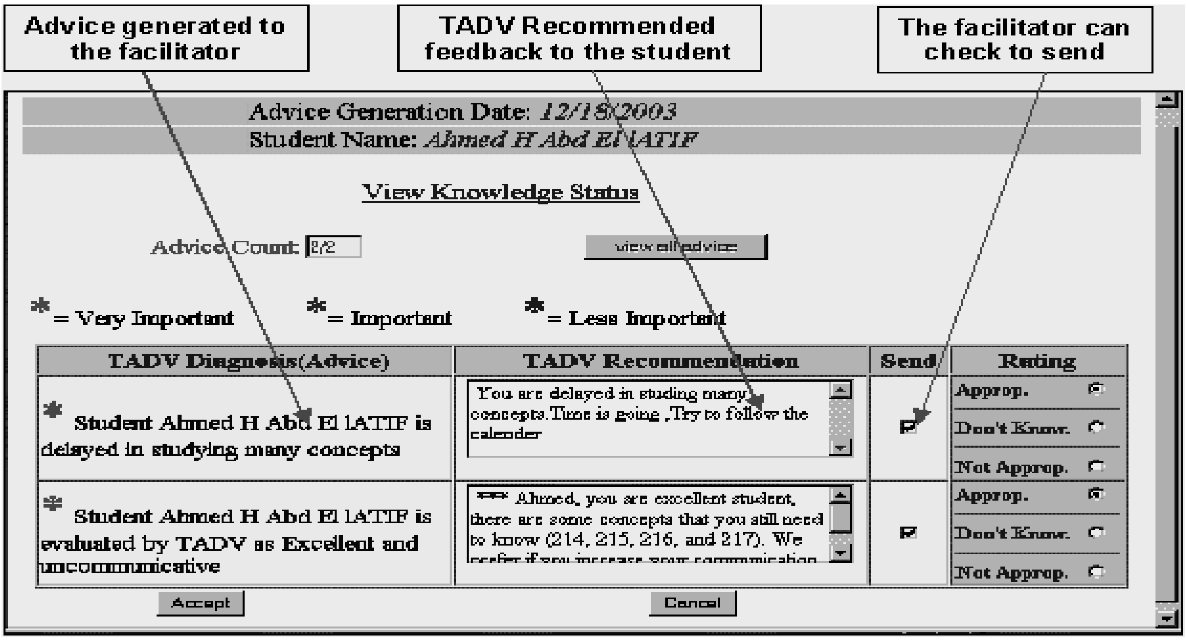

Figure 6. A screen used to display advice to the facilitator. Advice is offered to the facilitator, along with recommended text that can be sent to the student. The facilitator can modify the recommended advice before sending it and can choose either to send or suppress it. The rating section is for evaluation purposes.

6.5.2 Student's main menu

The student's main menu includes the following options:

Interacting with the course: The "My Learning" option is the location from where the student can interact with the course and assessment quizzes. This option allows the student to select either "My Course" or "My Assessment". Using "My Course", the student can go to CENTRA, start working with the assigned concepts, open the available learning objects, and communicate with student and teacher through the discussion forums. Using "My Assessment", the student can display the list of assessments available for each course lesson, and then simply select assessments;

Viewing the course calendar: The student can view the course calendar using the "Course Calendar". This shows the tasks that he/she should carry out in a certain period of time. In the TADV prototype, the tasks are scheduled by the course facilitator for each day of the course period;

Viewing assessment scores: The student can click on the "Assessment Score" option to view the assessments he/she solved and the scores obtained;

Contacting other students: The student can use the option "My Peers" to view a list with the names, phones and e-mails of the student peers in his/her group or class. The student can easily send e-mails to his/her peers;

Viewing feedback from the facilitator: The student can use this entry to review the feedback/advice sent from the facilitator through the TADV system. The student can display advice sent especially for him, and also the advice sent to the group and class to which he/she belongs. To facilitate evaluation of the TADV prototype (see Section 7) students are asked to rate the feedback they receive. Figure 7 shows a screen used to display advice and feedback to a student.

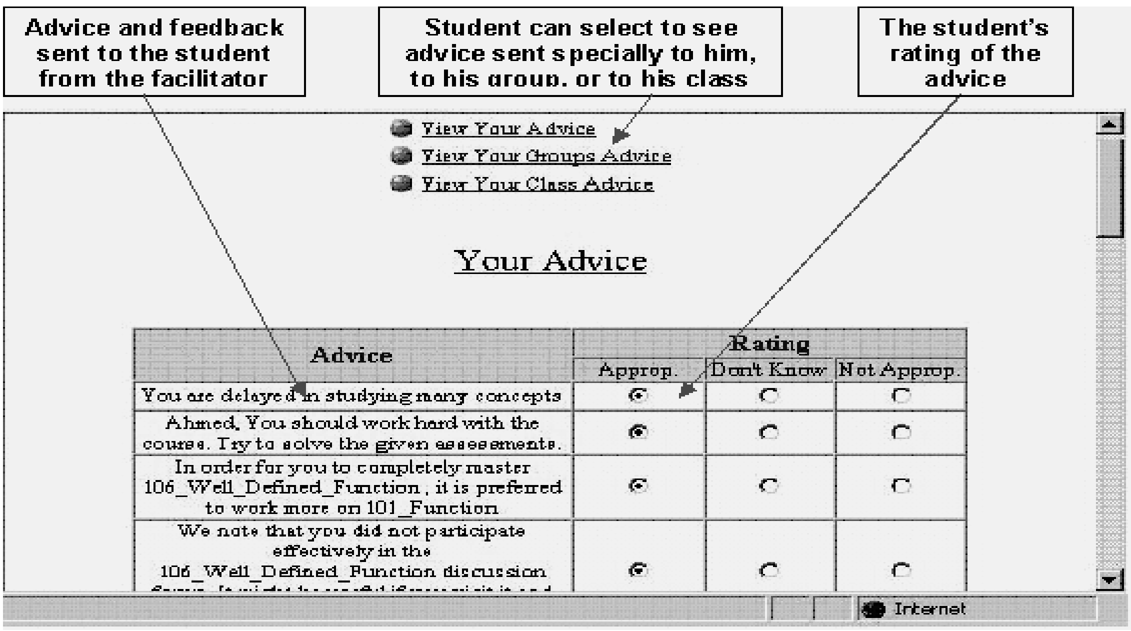

Figure 7. A screen to display advice to a student i.e. what the teacher has sent to this student.

7. Evaluation with students and teachers

The TADV evaluation aimed at verifying the usability and functionality of the system and examining the benefits of the approach for facilitators and students. It comprised a formative and a summative phase (Mark & Greer, 1993). The formative evaluation focused on the system performance. TADV was used by several students and teachers whose comments and suggestions helped improve the system for the summative phase presented here.

The summative evaluation examined the benefits of the approach by integrating TADV within a distance learning environment in a Discrete Mathematics course at AAST. Three facilitators[6] and 30 students took part in the study. The course material and the communication with the students were in English, which was familiar to all participants. Due to limitations imposed by the university administration, TADV was used three weeks and only for two topics of the course (Functions and Relations), the other topics being taught in traditional face-to-face lectures. The students were divided into two groups of 15:

- *Control group* (*Class-1*), where the students worked with TADV via distance. The system built models for them but the advice generation was suppressed. Consequently, the facilitators were not advised (i.e. students in this group experienced traditional use of WCMS and received feedback from facilitators through discussion forums and e-mail);
- *Experimental group* (*Class-2*), where the students worked with TADV via distance. The system built models for them, generated advice to the facilitators (the facilitators were the same for both groups) who then sent feedback to the students. The group allocation ensured equal distribution of student knowledge, academic background, gender, and nationality.

During the study, extensive data was collected, including log files, pre and post test, teacher interviews and observations, and student questionnaires. Qualitative and quantitative analysis was undertaken. A detailed description of the evaluation study with a comprehensive analysis of the results and a discussion of pedagogical benefits of TADV is presented in Kosba (2005). We will present here a summary of part of the results and a brief discussion of the benefits of TADV related to encouraging communication and peer help based on cognitive and interactive characteristics of individuals and groups.

7.1 Examples of advice generated during the study

Several examples of advice generated during the study will be presented to illustrate how TADV helped the facilitators to understand problems of individuals, groups, and the whole class, and aided the management of the course. Each example includes advice generated to the facilitator, recommended advice/feedback to the student (if any), explanation of the situation, including the facilitator's reactions, and the expected effect on the students. The examples follow the illustrations in sections 4.4. and 4.5. We focus on advice that directs students to communicate with their peers and to seek help.

[6] One of the facilitators was the teacher of the course for both groups, the second was the teacher assistant also for both groups, the third one was the main teacher for this course in the college and he was the domain expert who participated in the preparation of the metadata and fuzzy parameters required for this project.

Examples of advice related to individual students (Type-1)

The following examples show some situations of Type-1 advice generated to suggest possible communication activities to help struggling students or excel advanced students. The students are numbered in order of appearance to disguise their names.

Example (1): Excellent but uncommunicative student.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student S_4 is evaluated by TADV as Excellent and uncommunicative.</td><td>*** Well done S_4. Try to help your peers[7].</td></tr>
<tr><td colspan="2">Explanation: TADV found that S_4 is excellent but uncommunicative. TADV sent this information to the facilitator. The facilitator wrote and sent the shown feedback to S_4.
Results: The facilitator became knowledgeable about S_4. He composed the shown feedback and sent it. The facilitator used the knowledge he received to encourage S_4 and motivate him to be more communicative with his peers. Possibly, S_4 felt that the facilitator recognized his good work on the course.</td></tr>
</table>

Example (2): Weak and uncommunicative student.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student S_1 is evaluated by TADV as Weak and uncommunicative.</td><td>*** S_1, you should work hard with the course. Try to solve the given assessments. You should also communicate with your peers through the discussion forums for each concept</td></tr>
<tr><td colspan="2">Explanation: TADV found that the student was weak and uncommunicative. TADV sent this information to the facilitator, who used it to compose the feedback to the student.
Results: The facilitator got the knowledge and used it to motivate the student. The facilitator composed the shown feedback and sent it. The student realized that facilitator was aware of his bad performance. This may motivate him/her to work harder on the course.</td></tr>
</table>

Example (3): Encourage a student to communicate with his peers.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student S_2 should be encouraged to participate effectively in the communication activities related to ONE-TO-ONE FUNCTION. Student S_4 is communicative and has already mastered the concept ONE-TO-ONE FUNCTION.</td><td>We note that you did not participate effectively in the discussion forum related to ONE-TO-ONE FUNCTION. It may be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact S_4 to discuss ONE-TO-ONE FUNCTION.</td></tr>
<tr><td colspan="2">Explanation: TADV found that the concept ONE-TO-ONE FUNCTION was learned (but not completely learned) by the student S_2 and he/she did not participate in the discussion forum related to this concept. TADV located a student (S_4) who had mastered the concept and recommended that S_2 should be encouraged to contact S_4. TADV summarised the situation to the facilitator and recommended feedback to be sent to the student.
Results: The facilitator was informed of the problem and was recommended the solution. The facilitator sent the suggested feedback. The student was directed to communicate with his peer. Most importantly, he felt that he got help from the facilitator and he was not isolated in the distance course.</td></tr>
</table>

Examples of advice related to groups of students (Type-2)

The examples here are selected to illustrate how the facilitators used the TADV advice, based on knowledge status and communicative characteristics of a group, to motivate the group and to encourage communication among group members.

[7] Note that the facilitator advises the student to generally participate in different discussion forums rather than to help a specific student.

Example (4): A group needs to discuss more about a concept.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback the group members</th></tr>
<tr><td>Group G members should be encouraged to participate effectively in the communication activities related to ONE TO ONE FUNCTION.</td><td>We note that some students from Group G did not participate effectively in the discussion forum about ONE TO ONE FUNCTION. You will benefit from participating together in the discussion forum. You can post your questions there.</td></tr>
<tr><td colspan="2">Explanation: TADV found that group G was uncommunicative about concept ONE TO ONE FUNCTION. TADV informed the facilitator and recommended the shown feedback.
Results: The facilitator become more knowledgeable about this group and decided to send the generated feedback to the group members. The students were guided to contact each other and participate in the discussion group of the specified concept.</td></tr>
</table>

Example (5): A group struggles with a concept and most students have not mastered its prerequisite.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback the group members</th></tr>
<tr><td>Group G struggles with INVERSE OF ONE TO ONE FUNCTION. Group members should be advised to study ONE TO ONE FUNCTION.</td><td>INVERSE OF ONE TO ONE FUNCTION appears to be a common problem for students in group G. For those students who did not master INVERSE OF ONE TO ONE FUNCTION, it is highly recommended to study the perquisite ONE TO ONE FUNCTION first.</td></tr>
<tr><td colspan="2">Explanation: TADV found that group G was struggling with INVERSE OF ONE TO ONE FUNCTION because ONE TO ONE FUNCTION was unlearned by the group. TADV generated the shown advice and recommendation.
Results: The facilitator received the information and decided to send the generated feedback to the group members to study ONE TO ONE FUNCTION.</td></tr>
</table>

Examples of advice related to the class (Type-3)

On several occasions, the facilitators used the information from TADV to post messages to the whole class. Some of these situations are presented here.

Example (6): Majority of the class members delayed with starting the course.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the students</th></tr>
<tr><td>TADV can not evaluate class C because most of its students have not started course yet.</td><td>*** For all students who have not started the course, the time is going. Please start the course as soon as possible.</td></tr>
<tr><td colspan="2">Explanation: TADV found that most of the students did not start the course and informed the facilitator who composed the shown feedback.
Results: The facilitator received the information and decided to send the shown feedback to the class. This may motivate the students to start the course. In addition, the facilitator can contact students via e-mail.</td></tr>
</table>

Example (7): Excellent and weak students.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the students</th></tr>
<tr><td>Students S_4 and S_5 are the most Excellent students relative to the whole class, while S_1, S_2, and S_6 are evaluated by the system as the most struggling students.</td><td>*** To all class members: There are many students who did not start working with the course; this makes the class evaluated by the system as Weak. Please, those students should start the course as soon as possible. Most students should work hard with the course, solve the given assessments, and communicate with other students through the discussion forums prepared for each concept. Students who face problems can communicate with S_4 and S_5 who are ahead with the material.</td></tr>
<tr><td colspan="2">Explanation: TADV informed the facilitator about the most excellent and most weak students in the class. The facilitator composed the feedback.
Results: The facilitator read all advice generated about the class, not just the shown one. He received information about the class and composed the shown feedback to the class. This may motivate students to actively work on the course. It is noted here that the facilitator preferred to encourage excellent students but did not name the weak ones. However, he might be more encouraging with the struggling students.</td></tr>
</table>

The examples above illustrate how teachers used recommendations from TADV directly or composed messages based on the information they gathered from TADV feedback. In many cases, the teachers encouraged students to attend discussion forums or to communicate with their peers. It was noted that the facilitators could pay attention to both struggling and advanced students and undertook actions to help the former improve their knowledge or to praise the latter and encourage them to communicate with others.

7.2 Suitability of advice types

Examining the suitability of advice is needed to validate the whole framework, including the student and group modelling and advice generation algorithms. Suitability of advice was measured by considering aspects like what the facilitators thought about the advice features, how they evaluated the generated advice, what advice they sent to their students and how the students evaluated the feedback they received. When evaluating suitability of advice, we focused mainly on the usefulness of the advice for the teacher, as well as whether the advice correctly reflected the students' status and gave valuable information which helped teachers to better manage their distance class.

Table II shows a summary of the number of advice pieces generated to facilitators and sent to students, and the results of advice rating with respect to each advice type. The rating results are summarized in Figure 8. The results about each advice type are discussed next.

Table II. Number of advice pieces generated to facilitators and sent to students and advice rating by facilitators and students according to advice type. (A: Appropriate, D: Do not know, N: Not Appropriate)

Advice Type	**No. of Advice**	**Facilitator Rating**			**Sent Advice**	**Student Rating**		
		A	**D**	**N**		**A**	**D**	**N**
1-1 (student's knowledge status	348	188	156	4	189	57	35	6
1-2 (Student's Delays)	52	52	0	0	50	40	0	0
1-3 (Weak students)	47	47	0	0	45	33	0	0
1-4 (Excellent Students)	6	6	0	0	5	3	1	0
1-5 (Student not started the course)	82	82	0	0	77	6	0	0
Total Type-1 (Related to individual students)	**535**	**375**	**156**	**4**	**366**	**139**	**36**	**6**
2-1 (Group knowledge status)	127	32	95	0	16	21	9	3
2-2 (Weak group)	3	3	0	0	3	7	0	0
2-3 (Excellent group)	0	0	0	0	0	0	0	0
2-4 (Group members not started the course)	11	11	0	0	11	3	3	1
Total Type-2 (Related to groups of students)	**141**	**46**	**95**	**0**	**30**	**31**	**12**	**4**
3-1 (Class knowledge status)	104	71	33	0	1	5	5	0
3-2 (Excellent/weak students relative to class)	7	6	1	0	2	14	7	0
3-3 (Communicative students relative to class)	7	6	1	0	0	0	0	0
3-4 (Active and Inactive students)	7	6	0	1	0	0	0	0
3-5 (Class members did not start the course)	5	5	0	0	5	11	10	2
Total Type-3 (Related to the whole class)	**130**	**94**	**35**	**1**	**8**	**30**	**22**	**2**
Total ALL	**806**	**515**	**286**	**5**	**404**	**200**	**70**	**12**

A total of 570 pieces of advice of Type-1 (Individual student level) were generated; from those 35 were filtered out by TADV because they were considered as redundant. Accordingly, a total of 535 pieces of advice of Type-1 were displayed to the facilitators and rated by them. The facilitators and the students rated all advice pieces of Type1-2 (student's delays), Type1-3 (weak student), and Type1-5 (student has not started the course) as "Appropriate". There were only four pieces of advice of Type1-1 rated by the facilitators as "Not Appropriate". They related to situations when students were struggling with several prerequisite concepts for a concept and TADV generated advice for each prerequisite. The facilitators in the study felt that it was sufficient to display the first advice and suppress the rest or to just combine the several pieces of advice about prerequisite concepts into one. This suggests the need for *filtering* advice pieces. The facilitators rated all Type1-4 (excellent student) advice as "Appropriate". The students rated only half of the generated Type 1-4 advice as "appropriate" (3 out of 6) while they rated 60% of the sent Type 1-4 advice as “appropriate” (3 out of 5). The analysis showed that this was due to the fact that excellent students were unaware of how communicating with others would be beneficial. This suggests the need for developing collaborative spirit and motivating the students to share their knowledge with peers. Although this could be done by the teacher, some *motivational factors* could be added to the advice generated by TADV.

A total of 158 pieces of advice of Type-2 (Group level) were generated, from which 17 were filtered out. Accordingly, a total of 141 were displayed to the facilitators. 127 pieces of advice of Type2-1 (group knowledge status) were displayed and rated by the facilitators. Although there were advice pieces rated as “Not appropriate”, 75% were rated as “Do not know”. The analysis revealed that these situations were related to Group 1, evaluated by TADV as weak. The facilitators felt that there were too many advice pieces highlighting problems of students with a number of concepts. Although this information was correct, the facilitators thought that it was unnecessary to send too many negative messages. Instead, they decided to compose one message that encouraged all group members to work on the course. This points at the need to *aggregate* similar situations in one piece of advice. Accordingly, the amount of Type2-1 advice sent to the students was low. The students rated 64% of what was rated from this type as “appropriate”. Most advice pieces which were rated as “Not Appropriate” or “Do not know” relate to situations when most group members were struggling with a concept. In these cases, TADV informed the facilitators about the problem and they composed a message to the whole group to encourage everybody to study the concept. For those students who had already studied the concept, this group message may not have been applicable; hence, they have rated it as “Not Appropriate” or “Do not know”. Similarly, the students rated Type2-4 advice pieces (most group members did not start the course, all rated as “Appropriate” by the teachers and sent to the students) as “Not Appropriate” or “Do not know” when advice was sent to the whole group to start the course while particular students had already started the course. It should be noted that the facilitators in the study used the group advice to create the feeling that the students belonged to a group. Other facilitators might find that a group message is not needed because the individual students have already been sent relevant Type-1 messages. The facilitators and the students rated advice pieces of Type2-2 (weak groups) as “Appropriate”. In this experimental study, the two groups allocated by the facilitators were evaluated by TADV as weak. Therefore, no advice from Type2-3 was generated.

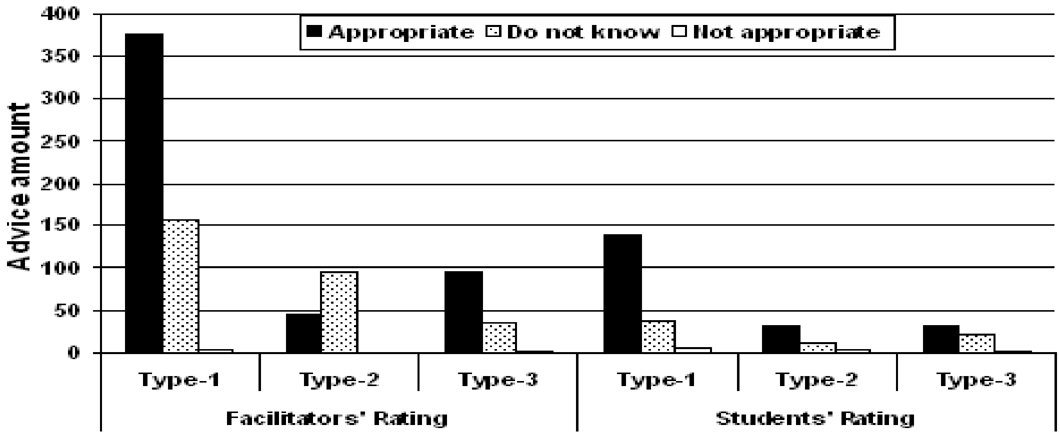

Figure 8. Advice rating results. Type-1, Type-2, and Type-3 concern individual students, groups of students, and the whole class, respectively. The teachers rated all advice generated by TADV, the students were required to rank the advice pieces that the teachers sent to them. However, there were times when the students received advice but did not rank it.

A total of 130 pieces of advice of Type-3 (Class level) were generated to the facilitators. In the current implementation of the TADV prototype, the facilitators were informed about problems with the class but were not suggested text to send to the students (it was expected that the facilitators would formulate appropriate feedback based on the knowledge about the class they gained with TADV). It was observed that in most cases for Type-3 advice, the facilitators read the delivered information, and, accordingly, composed and sent one or two messages to all students. Therefore, there was no direct relation between the amount of advice rated by the facilitator as appropriate, and the amount of advice sent to the students. The facilitators in the study formulated mostly general feedback to the whole class without highlighting weak or passive students. Although there were no advice pieces of Type 3-1 (class knowledge status) rated as “Not appropriate”, the teachers rather 32% as “Do not know”. Similarly to the group case, the facilitators reported that when the class was evaluated by TADV as weak, and the amount of generated advice increased significantly, it would have been better to generate only one piece of advice to highlight the situation. This again indicates situations when advice *filtration* could have been beneficial. Despite the fact that the facilitators rated 71 pieces of advice of Type3-1 as “Appropriate”, they only sent one piece of advice of this type to the class. This shows that although the advice reported correct and important information about the class, the facilitators in this study preferred not to send each pieces of advice to the students, but composed a summarized feedback. The facilitators rated 86% of Type3-2 advice (excellent and weak students relative to the class) and Type3-3 advice (communicative and uncommunicative students relative to the class) as “Appropriate”. One piece of advice from each type was rated as “Do not know”, due to a grammar mistake in the advice template, which lead to misunderstanding of the advice. The facilitators composed and sent feedback as a result to 2 pieces of advice from Type3-2. The students evaluated the facilitators’ feedback – 14 as “Appropriate” and 7 as “Do not know”. We could not find a reasonable explanation for the “Do not know” ratings. The facilitators did not send any feedback directly from Type3-3 advice, but they felt that the information provided in this advice type was important for gaining a better understanding of the class. 86% of Type3-4 advice (Active and Inactive students) was rated as “Appropriate” by the facilitators. Only one piece was rated as “Not appropriate” because some students were considered as both active and inactive in the same advice due to a programming error. This was subsequently fixed. As in the case of Type3-3, the facilitators did not send any feedback directly from Type3-4 advice but they felt that the information highlighted by TADV was helpful. All 5 pieces of advice of Type3-5 (most class members did not start the course) were rated by the facilitators as “Appropriate” and were sent to the class. The reasons behind the students’ rating as “Not appropriate” or “Do not know” are similar to those discussed about the group advice (see Type2-4 above).

The teacher interviews and the student questionnaires were also used to analyse the suitability of advice. Due to space limitations, we will only summarize the main findings (a comprehensive description is given in Kosba (2005)):

- The facilitators were satisfied with the advice generated by TADV regarding advice types, contents, and the situations addressed. The facilitators appreciated the generated advice and agreed that it was needed and useful.
- The students found that advice was suitable and guided their learning activities. As most helpful, they regarded the feedback that pointed out the delayed or struggling students. Some students asked for advice to be generated on a daily basis, and others suggested the advice to be in Arabic.

- Type1-2 (student delays), Type1-5 (student did not start the course), Type2-4 (most group members did not start the course), and Type3-5 (most class members did not start the course) was regarded as appropriate and helpful by both teachers and students. This shows the importance of advice related to students' behaviour with the course.
- The appropriateness of Type1-3 (Weak student), Type1-4 (Excellent student), Type2-2 (Weak group), and Type3-2 (Excellent and Weak students relative to the class) show the importance of the automatic student evaluation mechanisms for the facilitators.
- The study showed the appropriateness and the importance of the advice types related to students' knowledge status [Type1-1 (student knowledge status), Type2-1 (group knowledge status), and Type3-1 (class knowledge status)]. However, for these types of advice the facilitators stressed the issue of reducing the pieces of advice in some situations (e.g. when a student was struggling with many concepts, the corresponding number of advice pieces were generated, while the teachers preferred one piece of advice to highlight that this student was struggling with the course concepts). This shows the need to add some advice filtration and aggregation mechanisms.

7.3 Benefits for facilitators

TADV is directed towards helping facilitators to appropriately manage their distance classes through providing them with important information about the behaviour of their distant students. The facilitators' feedback was considered as crucial part in the evaluation. It was gathered during the advice generation sessions and via a group interview at the end.

Although the study time was limited, the facilitators felt that by using TADV as a framework for Web-based learning it was possible to achieve similar learning gains to what would have been achieved in a face-to-face learning environment. However, they pointed out that the learning gains could not be attributed solely to the interaction with TADV because some students did not use the available learning objects and others used TADV just to solve the available assessment quizzes. This is valid for all online distance education environments in which students can freely study on their own using the online material, printed material, textbooks, or any supplementary materials they find.

The facilitators regarded the fact that when using TADV, they became aware of the cognitive status and behaviour of their distant students as very positive, as one of them commented:

> "*Class-2 seems clear to me - I can easily know who is delayed, who did not start the course, who is good and who is weak. I can also know what concepts students are struggling with.*"

Through the generated advice, facilitators became aware of the following issues:

- Problems with individual students, groups, and whole class, e.g. which concepts students were struggling with;
- Students' behaviour – who followed the course calendar, who was delayed, who was starting study just before the course ends, and who did not start the course;
- Students' knowledge status as judged by the system – how the students were progressing with the course material and what their communication status was.

It was difficult to compare the teachers' communication overload that resulted from both classes because the number of exchanged e-mails was very limited (the facilitators received 6 e-mails from Class-1 students and 2 emails from Class-2 students). The limited number of e-mails can be explained by the short experimental time and by the students' unfamiliarity with using e-mails to make contact with their teachers. This points to some cultural differences that may have to be considered in analysing student behaviour, which was not considered in TADV, and would require further studies.

The average time of an advising session was 54 minutes (STD 17). There were all together 7 advising sessions. Reading TADV advice and sending messages to the students did not consume much of the facilitators' time compared to the time the facilitators would have had to spend in order to gain the same understanding of their students by using only the monitoring features provided by WCMS.

7.4 Benefits for students

We have to acknowledge that within the short period of the experimental study, it was not realistic to expect a significant enhancement in the students' learning gains and their affective aspects. Nevertheless, we have been able to collect data that shows some potential benefits for students. Following are the most important outcomes concluded from the analysis of students' questionnaire, and pre-test and post-test scores:

- The percentages of students who thought that working with TADV was worse than face-to-face lecture was 62% in Class-1 (Control group) against only 29% in Class-2 (Experimental group). This might be attributed to the availability of the advice and feedback from the facilitators, which was the only differentiating factor between the two classes. The students felt the connection with the facilitator and appreciated the regularity of the feedback.
- The students were interested to know how they were evaluated by their facilitators. This stresses the students' need to receive feedback and get help from their teachers, which, in turn, shows the importance of providing support to teachers to give appropriate feedback to the students.
- Most students in Class-2 (62%) felt that they were continuously guided by the facilitators. Hence, using TADV led to forming the students' impression that the facilitators supervised them during the distance course. This can be linked to reducing the chance of being isolated and lost in the course.
- The availability of the advice reduced the students' need to contact their teachers.
- The level of student satisfaction with regard to the contact they had with the facilitator was higher in Class-2 (23% in Class-1 compared to 54% in Class-2). The students' satisfaction with the contact they have with their teachers is important for lessening the students' feeling of isolation in distance learning.
- Regarding the students' overall satisfaction, Class-2 responses were more positive than Class-1 responses regarding issues like enjoyment (31% in Class-1 vs. 77% in Class-2), self esteem (38% in Class-1 vs. 71% in Class-2), and recommending the course to other students (42% in Class-1 vs. 71% in Class-2).

7.5. Summary and general discussion

The experimental study has validated TADV and confirmed that it provides a useful extension to WCMS to aid teachers in both managing distance courses in a more effective way, and guiding distance students according to their behaviour and cognitive status. It has allowed generating advice to facilitators, which in turn made it easy to send individualized feedback to distance students. With TADV the facilitators were pointed to students who had not started the course, delayed, had not visited regularly the course material and assessment quizzes, did not communicate much in the course, excellent and weak students, and other important information about the groups and classes. The facilitators regarded the provided advice as useful for monitoring and managing successful distance education courses. The generated advice and the TADV recommended feedback to the students gave the facilitators the chance to appropriately help and guide their students without experiencing considerable cognitive and time overload. The study also confirmed the appropriateness of the advice types included in the proposed taxonomy and pointed out required enhancement for few advice subtypes. The students were pleased with the feedback received from the facilitators with the help of TADV. The study pointed out the need to reduce the amount of generated advice by employing appropriate filtration and aggregation mechanisms.

One of the important factors that affect the efficiency of the system is the types of advice that constitute the advice taxonomy used. The advice taxonomy in TADV was based on a limited study, including both review of related literature and interviews with several distance learning teachers, with some experience in teaching using WCMS environments. The taxonomy, described in Section 5, gives a general model for advice generating which may facilitate capturing of more advice types in the future. Studies may be conducted with a large number of distance teachers to develop a more general and comprehensive advice taxonomy based on the one currently used in TADV. It is worthwhile for the new taxonomy to consider improving the pedagogical actions recommended by the system with different advice types. In the taxonomy proposed in TADV, there are many advice situations, especially at a class level (Type-3) in which the system is not able to recommend the best feedback to the student and the action is left for the teachers' decision. These need further clarification in the future.

An important outcome that emerged from the TADV evaluation is the relation between the suitability of the advice type and some cultural aspects related to the students’ social behaviour. Further studies are required to deeply consider cultural aspects that may affect the structure of the advice taxonomy. It is necessary for the taxonomy to include different types of advice that cope with different groups of students from different cultures. Cultural aspects may be considered in the phrasing (language) of the advice templates. For example, in some cultures it may be useful for the advice to motivate and encourage the students, while in other cultures, advice may be more useful when it gives the students the impression that they are being continuously supervised and monitored by their teachers. Future work in this direction should consider socially appropriate advice, e.g. work on socially sensitive tutoring dialogues (Johnson et al, 2004) can be applied.

Further studies are needed to examine whether the students follow the advice sent to them by the facilitators; what changes these make; and if they affect the students' motivation and meta-cognition. To answer these questions, a long-term research is required to examine the link between the TADV advising features and methods for improving the student’s motivation (de Vicente and Pain, 2000; Del Soldato and Du Boulay, 1995) and meta-cognition (Chi et al., 1989; Conati and VanLehn, 2000).

Currently, the advice in TADV is based on students’ cognitive and communicative aspects, which are combined to suggest activities that excel the students’ knowledge, create stimulating atmosphere for peer helping, and improve group awareness. Although communication activities and group work could be suggested as a possible way to address cognitive problems of individual students or groups, group work and collaboration was not analysed. TADV was aimed for traditional classes where students familiarized with course material on their own and participated in discussion forums clarifying issues related to domain concepts. A further extension of the framework will be needed to not only offer communication activities but also to analyse the effectiveness of these activities and the pedagogical impact they have on the students, groups, and the class.

8. Related Work

The work presented here is aimed at supporting teachers in web-based distance learning. Several projects consider providing support for teachers in web-based learning environments. For example, Delozanne et al. (2003) and Merceron and Yacef (2003) apply data mining techniques to analyse students' answers and extract only common, pedagogically relevant information, which is used to provide feedback to teachers. Along the same line, Chang (2003) proposes an evaluation mechanism to perform quantitative analysis of exam outcomes to allow teachers to choose different instruction sequences, while Stevens et al. (2004) analyse a database with student's performances to inform instructors about problem solving processes undertaken by students. Commonly, these projects focus on a certain type of students' interactions. In contrast, TADV examines a variety of students' interactions and provides feedback about both cognitive and communication aspects.

The TADV goal to provide support to distance learning teachers based on information gathered from tracking data is similar to the goal of CourseVis (Mazza & Dimitrova, 2004). However, the approaches employed differ significantly. CourseVis uses information visualisation techniques to produce graphical representations of student tracking data, while TADV employs intelligent techniques to automatically generate advice. By highlighting important situations and recommending appropriate actions, TADV provides tailored support and, at the same time, lessens the teachers' cognitive and communication overload. Notably, the effectiveness of CourseVis depends on the teacher's ability to understand graphical representations which may sometimes require additional cognitive effort.

TADV demonstrates an original approach for utilising intelligent modules to extend the capabilities and improve the functionality of conventional WCMS. In this respect, TADV contributes to recently emerging research on intelligent WCMS, see for example Brusilovsky (2003), Capuano et al. (2000), Santos et al. (2003), and Sanchez et al. (2003).

To model the students' knowledge status and communication characteristics, TADV considers information derived from tracking data produced by WCMS. Similarly to Anjaneyulu (1997), Capuano et al. (2000) and Grigoriadou et al. (2002), we have considered plausibly certain information derived from students' answers to assessment quizzes that test different domain concepts. In line with ABITS (Capuano et al., 2000), InterBook (Brusilovsky et al., 1997), and AHA! (de Bra & Calvi, 1998), we have also considered uncertain information derived from students' interactions with learning objects. As an addition to existing approaches for dealing with uncertainty in student modelling, we have tuned the effect of uncertain interaction with learning objects to take into account the time a student has spent working with an object.

In most intelligent educational systems, students' interactions are considered as the main source for assessing the students' cognitive and social aspects. As mentioned by many researchers, e.g. (Shultz et al., 1989) and (Rich & Knight, 1993), the approach of certainty factors appears to mimic quite well the way people manipulate certainties and makes strong independence assumptions that make it relatively easy to use. Several approaches have been used to get useful interpretations from students' interactions in order to build fuzzy student models. For example, Anjaneyulu (1997) presents a framework for concept level modelling in a hypermedia application where a student's answers to questions related to a concept are used to evaluate the student's performance. Following a similar idea, Grigoriadou et al. (2002) propose a fuzzy logic-based decision-making model that stores and analyses uncertain information regarding the various characteristics of the student, and also evaluates his/her knowledge status and skills. The evaluation of the students' knowledge level and cognitive abilities is based on students' answers to pre-stored questions. In Capuano et al. (2000), when a student has read an expositive learning object (e.g. lesson) with a given set of concepts included in it, the system forecasts a slight increase of the student's knowledge of these concepts with a large degree of uncertainty. Similarly to these systems, we have exploited fuzzy techniques. Distinctively, TADV considers a variety of sources when diagnosing individual students and groups, which is in line with the discussion in Weibelzahl and Weber (2003) who point out that modelling knowledge status requires analysis of both the students' interactions with the learning material and the results of explicit assessment.

Finally, TADV can be related to research on modelling and supporting groups of students. This has been the prime goal of Computer-Supported Collaborative Learning, which provides support to groups of students working in a collaborative learning environment (for a recent review of collaborative learning systems see Soller et al. (2005)). Collaborative learning benefits a student through facilitating participation in group discussions and active contributions to a group project (Edelson et al., 1996). Systems for collaborative learning usually provide tools that facilitate online interactions, e.g. chat, bulletin boards, and discussion forums. These tools are good mechanisms for supporting conversations among students, but they rarely provide guidance or direction for the students during or after the dialogue sessions (Soller, 2001). The analysis of student behaviour in TADV could be a useful source to support group work and collaboration. In this vein, a much more elaborated approach to analyse collaborative behaviour in groups by utilising fuzzy techniques is presented in Barros and Verdejo (2000).

The group models in TADV are considered as instances of a student model (Paiva, 1997). The main difference is that an individual student model is extracted from the interactions of one specific student, while a group model is derived from the interactions of all group members. TADV considers only WCMS tracking data which is limited and makes it difficult to obtain information about the beliefs a student has about his/her colleagues, or actions a student takes with other group members. Consequently, the TADV group models focus only on knowledge status and simplify many of the components suggested in Paiva (1997).

9. Conclusions

The work presented in this paper is a step towards increasing the effectiveness of distance education with WCMS platforms through the use of student modelling and advice generation techniques. The paper introduced a teacher advisor framework - TADV – aimed at helping instructors to keep close to and effectively guide their distant students. We have described the courseware structure recommended for TADV. We have also described the student modelling features of TADV and the fuzzy approach used to diagnose the knowledge of individual students, groups, and classes. The TADV advice generation mechanism has been discussed and it has been shown that student models are crucial for providing teachers with helpful advice tailored to the specific conditions of the courses they run. The advice types and advice generation criteria proposed in this work are quite general, and are not dependent on a specific domain or WCMS used. An empirical study with a TADV instantiation in a Discrete Mathematics course showed that teachers have gained a better understanding of the needs and problems of their students, which may result in a more effective instruction and may lessen the students' feeling of isolation. The study also showed that the students appreciated the teacher's feedback, based on TADV recommendations. Currently, TADV is being instantiated within another WCMS being developed within AAST, and will be used by a large number of students and teachers. This will enable us to conduct studies involving a large number of users in a long period of time and to further examine the impact of TADV.

Acknowledgements

This work is sponsored by Arab Academy for Science and Technology and Maritime Transport - Alexandria - Egypt. Professor John Self's supervision at an earlier stage of this work is greatly acknowledged. The authors are grateful to the participants in the TADV evaluation study.

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