DE GRUYTER OPEN

ICTE Journal

2016, 5(1): 14–31
DOI: 10.1515/ijicte-2016-0002

EXPERT SYSTEMS AND ADAPTIVE PROCEDURES OF THE COMPUTER EDUCATIONAL SYSTEM ADEPT

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Abstract

Current pedagogical research has striven to create an adaptive computer educational system which would come closest to each student’s needs and skills, and would ensure the quickest and the most effective way of acquiring the necessary knowledge in the field concerned. Modern informational technologies are fundamental which make use of unconventional methods of artificial intelligence to mechanically and abstractedly formalize mental models of experienced educators, which leads to mechanical representation of their sophisticated teaching methods and procedures. The structure of the adaptive educational system includes fuzzy expert modules which formalize mental decision-making functions of an experienced educator. Two adaptive loops execute the processes of the adjustment of study materials according to the continuous study results shown and of learning the system according to the information about the student’s modified learning procedure.

Keywords

adaptive educational system, learning style, evaluation, expert systems, fuzzy model, model learning, adaptation

Introduction

In 1960s, knowledge from cybernetics and mainly algorithmization started to be implemented into the learning process. That is how the programmed learning was born and its basic idea is to control the student’s work completely. This form of schooling wasn’t extensively executed at that time owing to the lack of technical background. Only when microcomputers and later personal computers entered the scene in the 1980s, the programs following the programmed learning principles have developed significantly. Several expressions were used such as computer controlled learning, and computer assisted learning. These computers assisted learning systems (CAL) were complemented by artificial intelligence elements and tried to create a certain model of an artificial teacher.

In 1990s, there was a rapid development of informational and communication technologies, which influenced the educational field as well. After the Internet appeared, e-learning has expanded significantly. E-learning has served for individualization of learning, as each student prefers their own learning style. In order to individualize the learning, it is necessary to adjust it, or adapt it in accordance with the student's needs. The importance of this accordance between learning and a teaching style leads to better achievements; it also makes learning easier and increases the effectiveness of students' learning (Bajraktarevic, Hall, Fullick, 2003; Brusilovsky, 2003).

Adaptive learning system is such a system which tries to customize the schooling process to students' individual characteristics and needs. Its aim is to create such an environment which will motivate a student to such extent that s/he is willing to learn by himself/herself even if not forced. The system tries to accommodate the most to the student; it responds to his/her incorrect answers in a different way, explains the subject matter more slowly or in more detail. It also tries to draw the student's attention to his/her errors, give examples, etc. It will also inform the student clearly what s/he has to know and to what extent; if s/he has already achieved the required level of knowledge and which grade they will be awarded. In adaptive learning systems, there are artificial intelligence elements used for formalizing mental models of experienced educators – experts in the field of learning process government and management.

Relevant parts of the adaptive learning system (ADaptive Educational Programme Tool) are presented in the paper, which represent its decision-making and adaptive procedures. Decisive tasks of choosing the student's learning system and evaluation of the learning material suitability according to their individual learning style are executed using artificial intelligence tools – the on-line fuzzy-logic expert systems. The system includes two adaptation tasks. The first of these modifies student's learning material structure in the course of study according to his/her current results, the second adaptive loop continuously modifies the specification model of study material suitability according to its real effectiveness in the learning process.

The paper introduces the ADEPT system principles as well as results of simulative functional examination of both expert systems and functions of both adaptive loops.

Computer Learning System ADEPT

The basic structure of the computer educational system ADEPT is depicted in Fig.1. The simplified scheme is focused mainly on decisive blocks and adaptive loops which ensure increased system efficiency in the student's learning process.

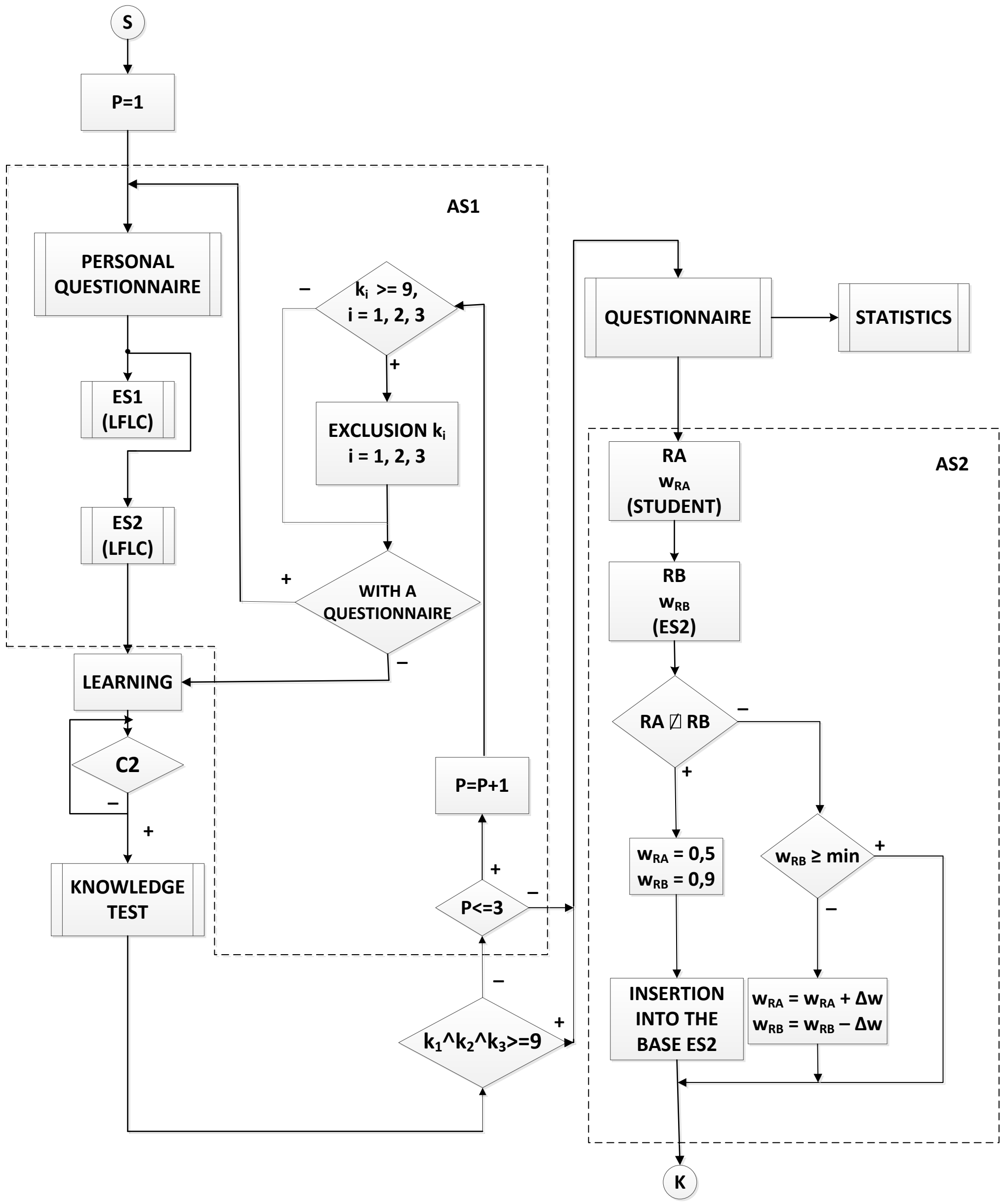

Fig. 1: The system ADEPT scheme

The system base consists of two on-line decision-making blocks which make use of fuzzy-oriented expert system technology (Buckley, Siler, 2005). Above all, the system recommends the student the most suitable version of study materials in agreement with his/her study type. On the basis of study results in particular cycles, it modifies the study materials in the first adaptive loop and carries out the student's final evaluation after his/her learning process has ended. In the second adaptive loop, it modifies the materials according to the learning rule for recommending study materials.

At the beginning, the student's study style is diagnosed before his/her expert system learning ES1 starts (preliminary diagnostics). Information about the amplitude of particular system input values is obtained in the form of results after the particular student has filled in the preliminary questionnaire called PERSONAL QUESTIONNAIRE. The student's learning style estimation is important information about his/her characteristics.

The information from the questionnaire further serves as an input for the expert system ES2 which recommends the student the most suitable study materials. After the procedure LEARNING is completed that is when the student's first cycle of learning finishes (p = 1) and when his/her current knowledge gets tested in the block called KNOWLEDGE TEST. If the evaluated results are not satisfactory, the student proceeds to the second cycle (p = 2) unless the number of his/her learning cycles (p = 3) is depleted. The system enters the first adaptive loop AS1 which will recommend modifications of the second cycle study materials on the basis of the existing evaluation. The student gets a chance to modify the second cycle materials by completing the diagnostic questionnaire again where s/he can modify (specify) his/her opinion on characteristics decisive for his/her learning style. After finishing the second learning cycle, student's current knowledge is evaluated and in case of need the learning cycle is repeated including the adaptation of the materials.

If the evaluation is satisfactory after finishing individual cycles or always when the student runs out of a prescribed number of cycles, learning is finished and the system enters the phase of the learning cycles' process being evaluated by the student in the block QUESTIONNAIRE. Its results are both saved in the data base STATISTICS and made use of in the second adaptive loop AS2 for modifying the expert system model ES2.

Detailed functions of expert systems ES1 and ES2 are described in Chapter 4 and Chapter 5 in addition to a description of adaptive loops AS1 and AS2's function.

Decisive Fuzzy Modules of the System

Expert Systems

Expert systems are computer programs which simulate experts' decisive activities when solving very complicated and problematically narrow focused tasks (Buckley, Siler, 2005). There is no doubt that their function is closely connected to both human and artificial intelligence. These systems are based on the idea of knowledge take-over from an expert (meaning his/her objective and subjective knowledge) and its convenient computer representation which would enable a computer programme to make use of this knowledge in more or less the same way the expert does.

The core of such a system (Fig.2) consists of a control (inferential) mechanism which specifies (updates) the general model and infers an answer – conclusion by making operations above the knowledge base on the basis of current data.

The knowledge base as a general behavioural model of the studied framework is made of expert knowledge formalized by a convenient representation.

An explanatory subsystem is a user-important part of the expert system. It provides information about a particular procedure which has led to the conclusion. This way the user can assess the quality of the knowledge base by himself/herself as well as the inferences; moreover, s/he can subsequently modify the inference result eventually.

It is possible to say that the aim of the expert system is to reach high-quality conclusions analogous to those of expert people in the particular field when dealing with complex problems.

Expert systems are capable of using efficiently possible uncertainties in both the knowledge base and the data base.

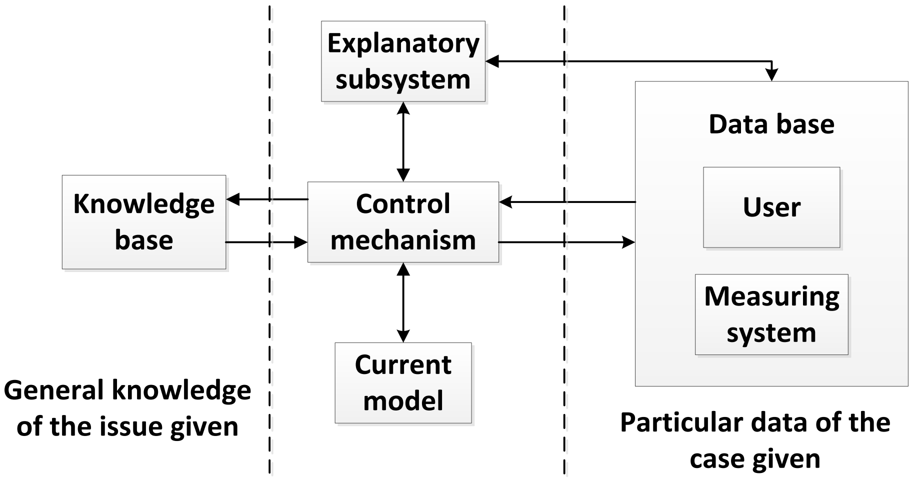

Fig.2: The expert system scheme

The typical characteristic of the expert systems is the skill to efficiently use uncertainty of unconventional models in indeterminate (vague) frameworks. The computer representation of expert knowledge (experts' mental models) has become the basis of these models. In a practical environment, expert systems which are very common are those using knowledge representation in the form of conditional IF-THEN rules and formalizing their uncertainties via mathematical fuzzy set apparatus. These models make use of linguistic fuzzy logic approaches (Buckley, Siler, 2005; Novák, Perfilieva, Močkoř, 1999) as inferential mechanisms.

Linguistic fuzzy modelling and inferences

If we consider the issue of creating a computer system which would deal with a particular problem so well as an expert (experienced educator) would, it is necessary to solve two basic tasks:

a) how to formalize subjective expert knowledge on the computer, or how to formalize the mental model on the computer,

b) on what principles to build logical algorithms which will function above this knowledge with the aim to use the linguistic model in a similar way the expert – educator uses his/her mental model.

The computer representation of linguistic descriptions requires using such methods which allow formalizing a very important characteristic of natural language words – vagueness, their natural uncertainty. Several methods have been developed to formalize vagueness, the most common of which is the method using fuzzy sets. We can easily express a meaning and vagueness of word concepts via fuzzy sets.

The linguistic rule fuzzy model is the basis of computer systems for expert cogitation simulation. The experience shows that any human knowledge can be expressed by means of language rules of the IF-THEN type (Novák, Perfilieva, Močkoř, 1999). The general form of the linguistic model rule is

IF (x is A) THEN (y is B), (1)

where fuzzy proposition (x is A) is a proposition of input linguistic variable size and is called the antecedent (condition, prerequisite), fuzzy proposition (y is B) corresponds to the size of output linguistic variable and is called the consequent (consequence, conclusion). The fuzzy logic rule (1) expresses the relation between linguistic variables x and y and can be simply interpreted as: If the linguistic variable x gains its linguistic value A, a status when another linguistic variable y gains its linguistic value B is the consequence.

In case of multiple input variables model, the statements about their size in so-called complex antecedent are tied by a fuzzy-logic connective fuzzy conjunction. When describing the framework including n-input variables x1 - xn and a single output variable y, we get a k-rules framework in this format:

R_1 : IF (x_1 is A_{11}) and (x_2 is A_{21}) and … and (x_n is A_{n1}) THEN (y is B_1)

R_2 : IF (x_1 is A_{12}) and (x_2 is A_{22}) and … and (x_n is A_{n2}) THEN (y is B_2)

R_k : IF (x_1 is A_{1k}) and (x_2 is A_{2k}) and … and (x_n is A_{nk}) THEN (y is B_k) (2)

Antecedents of rules usually contain all linguistic value combinations of input variables; a particular size of the input variable in consequent is decided by an expert.

The form of a modified output fuzzy set B0 when placing particular values of variables x1,0 to xn,0 is acquired by a deductive algorithm which uses fuzzy logic rules. Deductive algorithms differ in their interpretation of fuzzy-logic conjunctions (Buckley, Siler, 2005). A Mamdani type mechanism is used for drawing conclusions in the article concerning expert systems involved. The form of affiliation function of the output fuzzy set B(y) is determined by the relation

$$B(y) = \max_{1<r<m}\left(\min\left(B_r(y), \min_{1<j<n}\left(Cons\left(A_j x, A_{rj} x\right)\right)\right)\right) \tag{3}$$

An explanation of this operation called fuzzy composition can be found i.e. in (Buckley, Siler, 2005; Novák, Perfilieva, Močkoř, 1999).

The Expert System ES1

The expert system ES1 serves the diagnostics of a student's learning style before learning starts as well as later in the course of learning (Krišová, Pokorný, 2013).

A learning style is a learning procedure which a student uses in a particular life period in most pedagogically-oriented situations. Up to a certain degree, these are independent on the subject studied. They originate from congenital basis (cognitive style) and develop by co-operation of inner and outer influences. There is a huge amount of influences having an immediate effect on the student's learning style (Kostolányová, 2012). The proposed solution focuses on individual learning via e-learning and that is why the characteristics chosen for the student's learning style diagnostics are those which are utilizable in e-learning environment and can be directly used for managing electronic learning. In the expert system ES1 linguistic model, the student's learning style is set on the basis of these parameters – input linguistic variables: social aspect, information processing method, sense perception, and learning procedure (Table 1).

Linguistic variable	Id	Scope of universe	Linguistic values	Id
SOCIAL ASPECT	SA	[0,15]	INTROVERT	INT
			EXTROVERT	EXT
INFORMATION PROCESSING METHOD	ZZI	[0, 15]	THEORETICIAN	TEO
			PRACTICIAN	PRA
SENSE PERCEPTION	SV	[0, 15]	GRAFIC	GRA
			VERBAL	VER
LEARNING PROCEDURE	PU	[0, 15]	HOLIST	HOL
			PERFECTIONIST	DET

Tab. 1: Input linguistic variables of the ES1 module

SV – Sense perception describes which information form suits a student best. It characterizes the sense by which the student perceives the most, what way s/he understands and remembers the information best. The system is derived from the opinion that students gain information by visualization (pictures, symbols, diagrams) or listening (via sounds and words) (Felder, Silverman, 1988). ES1 recognizes two types of students:

- *Graphic type* remembers best what s/he sees – e.g. pictures, diagrams, timelines and so-called flow charts which show the graphic realization of e.g. steps the teacher will include in the class. Information might be forgotten if transferred to students only orally.
- *Verbal type* remembers much of what s/he hears and even more of what s/he hears and interprets afterwards. Discussions suit these students best as they learn a lot from them. They prefer oral explanations to visual demonstrations. They learn effectively by explaining things to others or listening to them.

SA – Social aspect characterizes the way of involvement in a surrounding social environment which the student prefers while studying. On the basis of this characteristic the system ES1 differentiates two types of students (Mareš, 2004):

- *Introvert* prefers self-study or work in pairs – learns with a colleague or friend. S/he does not seek a bigger group, s/he listens rather than enters a conversation.
- *Extrovert* focuses on contact with people and reality, s/he prefers learning in a bigger group, discussing with classmates, and seeks cooperation with people.

ZZI – Information processing method recognizes preference of theory or practical experiments. On the basis of this feature the system ES1 divides students into two groups (Sternberg, Grigorenko, 1999):

- *Theoretician* prefers theoretical deduction and deep thinking about newly-gained knowledge.
- *Practician* is an experimenter who prefers an active try-out of the knowledge gained, as practical as possible. S/he seeks a way to utilize each piece of information and what the information can be useful for.

PU – **Learning procedure** differentiates students according to what amount of information they are able to process at once. The system ES1 describes two types of students (Riding, Cheema, 1991):

- *Holistic type* tends to perceive situations globally, as overall ones. S/he focuses on large parts of general information, following them gradually to get to detail. S/he finds detail analysis difficult.
- *Detail-oriented (perfectionist, analytic) type* focuses on small parts of particular information out of which s/he composes the entire picture. S/he has a difficulty to understand a situation at a global scale.

The system ES1 also considers a **social aspect combination with the information processing method,** and defines other four student types: active type, reflexive type, actively-reflexive type and reflexively-active type. It employs the fact that complex psychological processes transferring perceived information to knowledge comprise of two categories – active experimenting and reflexive observation (Felder, Silverman, 1988).

- *Active type* cannot learn much from lectures, because they transfer information passively. S/he learns better in situations which allow group work and active experimenting.
- *Reflexive type* requires situations which provide opportunities to think over the information presented. S/he is a theoretician and prefers working alone or eventually with another person
- *Actively-reflexive type* – a theoretician who prefers group work (extrovert).
- *Reflexively-active type* – a practician (an experimenter) who prefers working alone (introvert).

The steps (Felder, Solomon, 2004; Mareš 2004; Novotný, 2010; Riding, Cheema, 1991; Sternberg, Grigorenko, 1999) serve as a source for the student's questionnaire, the analysis of which provides current numeral values of all four input variables in the system ES1. In the questionnaire, a scale was added to questions which expresses the degree of the agreement with the statement (a, rather a, b, rather b). Particular answers are ascribed from 0 to 3 points. The student can receive ranking between 0 and 15 points as each characteristic is tested in five questions. In the expert system ES1 linguistic model, the aforesaid access to the student type decision is formalized by three output linguistic variables with linguistic values described in Table 2.

Linguistic variable	Id	Linguistic value	Id
REFLEXIVE or ACTIVE TYPE	REF/AKT	REFLEXIVE	REF
		REFLEXIVELY-ACTIVE	RA
		ACTIVELY- REFLEXIVE	AR
		ACTIVE	AKT
VISUAL or VERBAL TYPE	VIZ/SLO	VISUAL	VIZ
		VERBAL	SLO
HOLISTIC or PERFECTIONIST TYPE	HOL/DET	HOLIST	HOL
		PERFECTIONIST	DET

Tab. 2: Output linguistic variables of the ES1 module

Knowledge base of the system ES1 is formed by the framework of conditional IF-THEN rules (2) the conditional parts of which symbolize all linguistic value combinations of input variables. Individual combinations were expertly assessed by assigning particular linguistic values of output variables. For example, the rule R1 has a form

R_1: IF (SA is INT) and (ZZI is TEO) and (SV is GRA) and (PU is HOL) THEN (REF/AKT is REF) and (VIZ/SLO is VIZ) and (HOL/DET is HOL)

it formalizes this knowledge:

If the student prefers individual and theoretical learning, remembers better what s/he sees and prefers big information clusters while learning, then the student is reflexive, visual and a holist.

The expert system ES1 is implemented in a developing environment LFLC (Linguistic Fuzz Logic Controller) (Dvořák, Habiballa, Novák, Pavliska, 2003). Linguistic values of input and output variables in the fuzzy rule model are represented by fuzzy sets (Fig.3).

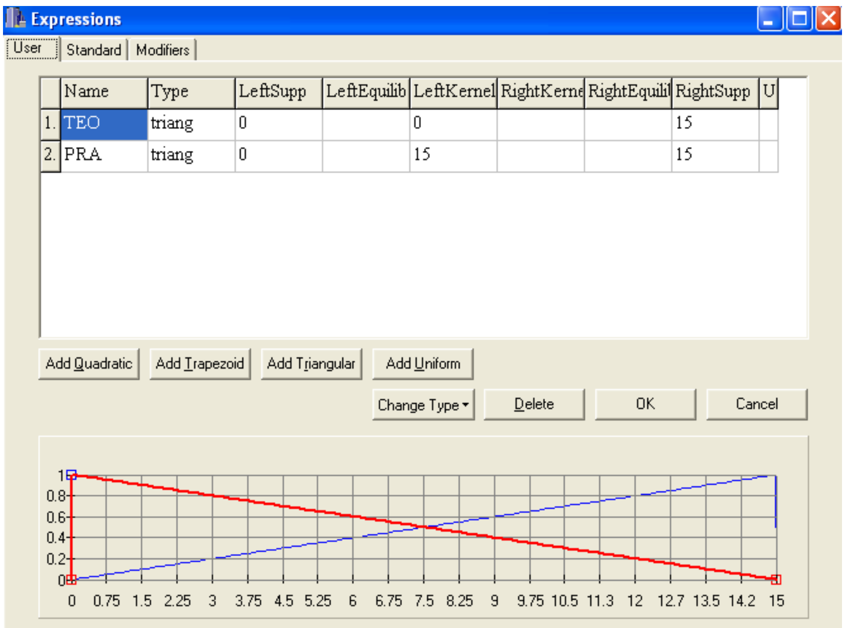

Fig. 3: LFLC image – input linguistic variables of the model ES1

Approximate deduction of the model's output linguistic values is carried out by the Mamdani method (Buckley, Siler, 2005. Learning styles become the output, assessed with options level <0,1> according to current values of outcome variables (Fig.4).

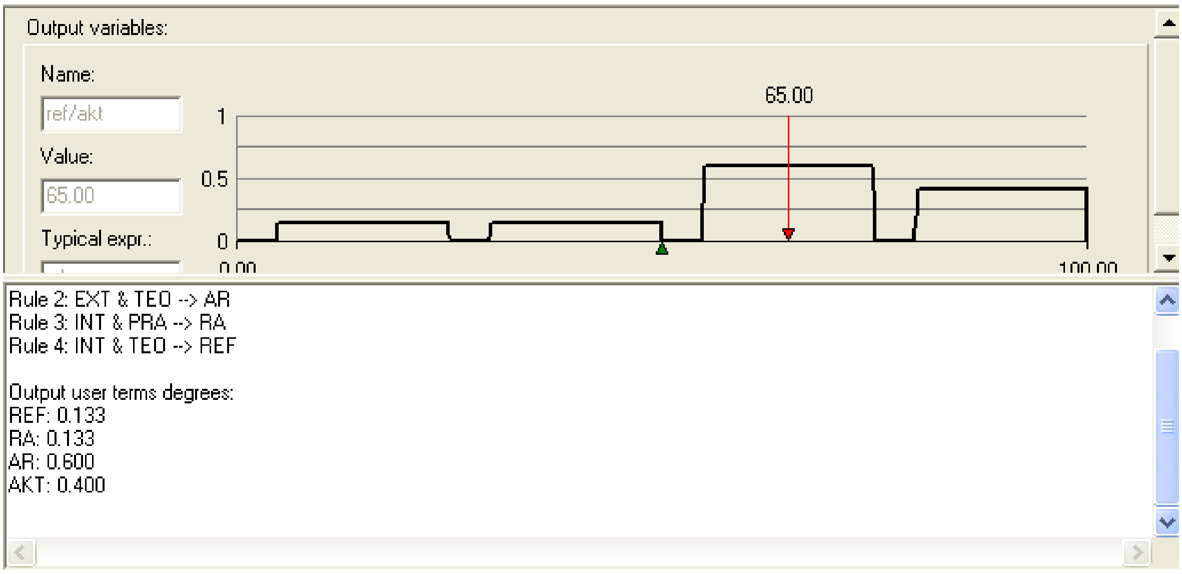

Fig. 4: LFLC image – assessed output values of learning styles ES1

The Expert system ES2

The expert system ES2 follows the system ES1. The expert system ES2 recommends the student a particular study material to learn from after evaluating the student's learning style by the system ES1. It results from the student's learning style – from the evaluated student's questionnaire.

The expert system ES2's linguistic model has 4 input linguistic variables (Table 1) and one output linguistic variable with 16 linguistic values which represent versions of recommended study materials (Table 3).

Variable	Id	Linguistic values (study types)
VERSION OF MATERIALS	V1	visual, reflexive and a holist
	V2	visual, reflexive and a perfectionist
	V3	visual, actively-reflexive and a holist
	V4	visual, actively-reflexive and a perfectionist
	V5	visual, reflexively-active and a holist
	V6	visual, reflexively-active and a perfectionist
	V7	visual, active and a holist
	V8	visual, active and a perfectionist
	V9	verbal, reflexive and a holist
	V10	verbal, reflexive and a perfectionist
	V11	verbal, actively-reflexive and a holist
	V12	verbal, actively-reflexive and a perfectionist
	V13	verbal, reflexively-active and a holist
	V14	verbal, reflexively-active and a perfectionist
	V15	verbal, active and a holist
	V16	verbal, active and a perfectionist

Tab. 3: Output linguistic variable of the module ES2

The expert system ES2 knowledge base is constituted by a file of IF-THEN rules (2) the conditional parts of which represent all combinations of input variables' linguistic values.

Individual combinations are expertly assessed by assigning particular linguistic values of an output variable. For example, the rule R1 has the form:

$R_{1:}$ IF (SV is GRA) and (ZZI is TEO) and (SA is INT) and (PU is HOL) THEN (VERZE is V1)

and formalizes this knowledge:

If the student remembers better what s/he sees, prefers individual studying and theoretical learning as well as big informational clusters, then I recommend the student to use the version V1 of study materials.

This rule thus concerns the visual, holistic and reflexive student (theoretician and introvert) who is assigned the version V1 of study materials according to Table 3.

The expert system ES2 is implemented in developing environment LFLC (Linguistic Fuzz Logic Controller) (Dvořák, Habiballa, Novák, Pavliska, 2003). Fuzzy sets of its input variables' linguistic values are shown in Fig. 6, of its output variables in the fuzzy rule model are represented in Fig. 6.

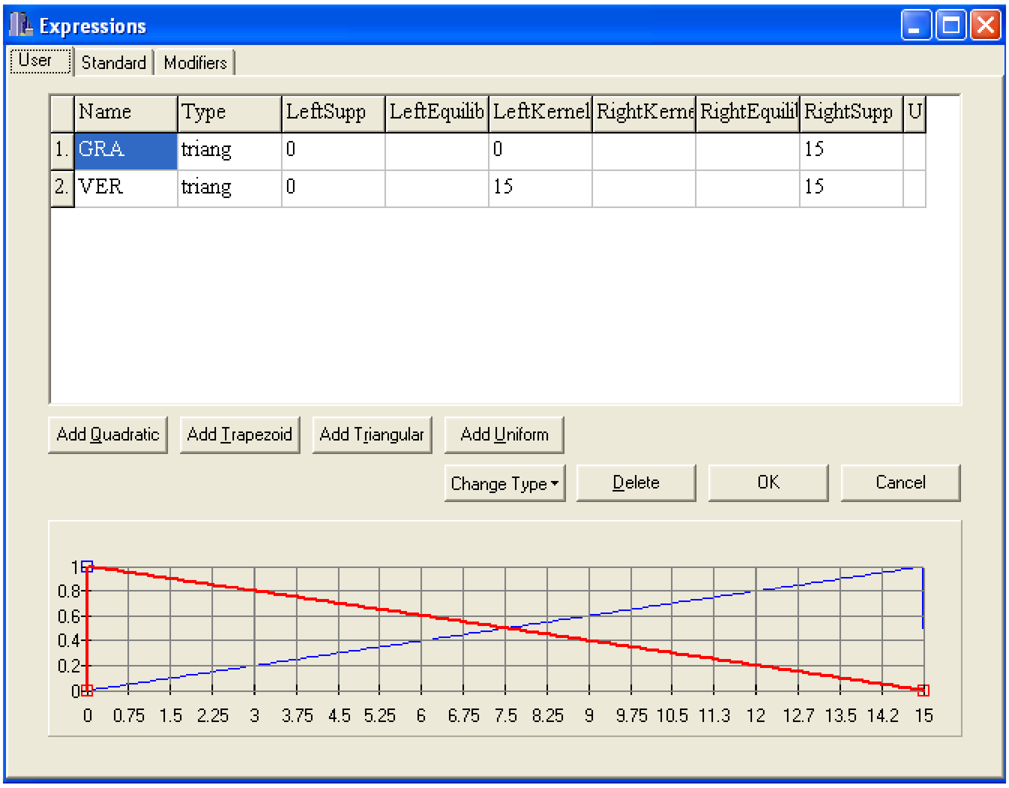

Fig. 6: LFLC image – input linguistic variables of the model ES2

Approximate deduction of the model’s output linguistic values is again carried out by the Mamdani method (3). Learning material variants become the output, assessed with suitability levels <0,1> for a particular student according to current values of outcome variables (Fig.7).

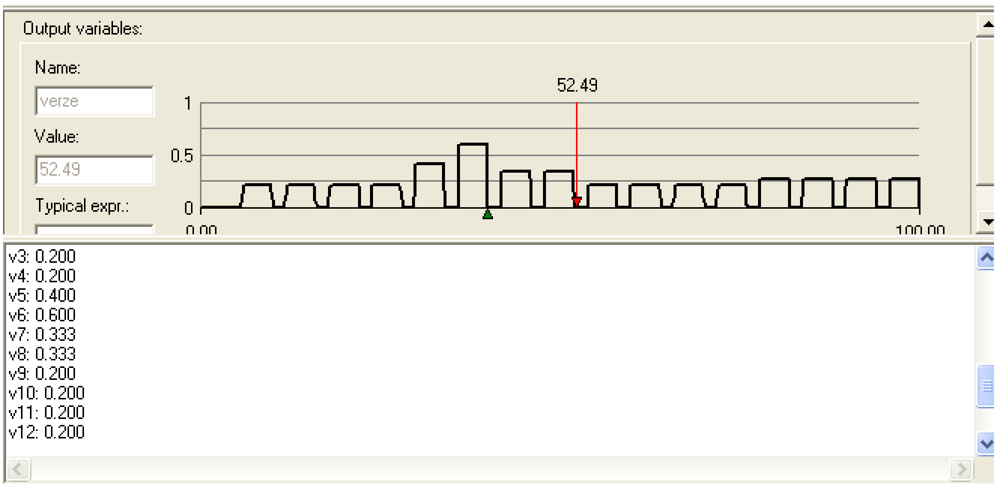

Fig. 7: LFLC image – assessed versions of study materials ES2

A particular version of recommended study materials V1 – V16 depends on the particular study subject. Chapter 6 introduces the linguistic model of the system ES2 which is targeted at teaching the subject Numeral systems.

System Adaptive Procedures

The Student's Learning Process Adaptation AS1

After evaluating the current level of the student's knowledge in the particular p- th learning cycle (the KNOWLEDGE TEST block) – see Fig. 1 – the student's knowledge is evaluated in the block R1 whether it is satisfactory in all studied chapters (three chapters in this case, named k1, k2, k3). If yes, the system offers the student an output questionnaire to fill in (QUESTIONNAIRE). If not, exhaustion of the number of granted learning cycles (R2) is checked and the system continues by pinpointing those study chapters which showed unsatisfactory results (R3). Furthermore, study materials for the next cycle are restricted and put forward to the student to learn. Simultaneously, s/he has an option to refill the questionnaire (PERSONAL QUESTIONNAIRE) and react on suitability of recommended materials by modifying answers to its questions. It is another option for the adaptive loop AS1 to modify the next learning cycle materials.

The expert module ES2 adaptation

In the course of the system ADEPT exploitation, the initiatory linguistic model of the expert module ES2 declared by an expert is modified (defined) by extending the number of its rules, or broadening the knowledge scope used for making decisions about suitability of individual 16 types of study materials (V1 – V16) for the particular student (Fig. 7).

The linguistic model contains 16 IF-THEN rules, the i- th rule of which recommends the material Vi in its consequent, i = 1,…,16.

After the last learning cycle is finished, the student fills in the form QUESTIONNAIRE in which s/he confirms or changes the order of material suitability previously recommended by the system ES2. If the student does not utilize for learning the material with the highest rank and, after consideration, s/he substitutes it by another one, then the new rule is generated which reflects this fact (knowledge) (RULE ASSIGNMENT).

If such a rule does not exist in the base (block R5), it is described as a NEW RULE and with lower weight of its influence (w = 0,5) it is inserted in the base ES2.

If such a rule does exist, this fact is taken into account only by rising the weight of its influence ($w = w + \Delta w$). After a prescribed number of occurrences of such a new rule the rule reaches the full influence (w = 1) in the base. Simultaneously, influence weight of the initiatory rule (determined by an expert) is being reduced. The learning function of the rule model ES2 is executed via this adaptive procedure. In Chapter 6, the function of the loop AS2 is also explained using a simulating process.

Simulative Verification of Decisive Procedures

Effectiveness of proposed fuzzy modules is verified in the Matlab-Simulink programme environment which is compatible with LFLC. The Simulink system is an upgrade of MATLAB for dynamic systems' simulation and modelling (Matlab, 2012).

The Expert System ES1

Simulation calculations in the adaptive learning system are carried out by filling in the questionnaire ES1, machine evaluation of which gives us concrete numerical values of four variables SA, ZZI, SV and PU. These values become inputs in the module ES1. ES1 derives appropriate values of three output variables. Table 4 introduces particular input values for simulating experiments.

Experiment no.	SA	ZZI	SV	PU
1	6	4	10	7
2	9	13	5	11

Tab. 4: Values of input variables ES1

Experiment 1 simulates the student who prefers individual studying and thinks about everything in detail. S/he remembers better what s/he hears or reads and focuses on big parts of general information in order to get an overall picture. The system has deduced correctly that the student is rather reflexive, verbal and holistic (Table 5).

Experiment 2 simulates a situation when the student prefers working in a group making attempts and errors. S/he remembers better what s/he sees and processes smaller information clusters. The system has deduced correctly that such a student is rather active, visual and a perfectionist (Table 5).

Experiment	Output linguistic values							
	REF/AKT				VIZ/SLO		HOL/DET	
	REF	AKT	RA	AR	VIZ	SLO	HOL	DET
1	0,6	0,4	0,27	0,27	0,33	0,67	0,53	0,47
2	0,13	0,6	0,4	0,13	0,67	0,33	0,27	0,73

Tab. 5: The student's learning style typology assessed by an expert

In both experiments, results of the student's learning style diagnostics corresponds with presumptions. They show an important characteristic of the system E1 – individual learning styles for the particular student are ascribed interconnected in interval <0,1> with a possibility to interpret the outputs in the form of orderings. This global output has a denser informational content than a pure estimation of the student's learning style allocated into an acute numeral interval.

The Expert System ES2

Study materials created for simulating verification deal with numeral systems (one of the topics from the subject IT for economists). Materials are divided into three chapters: Numeral systems issues, Transfer among numeral systems, and Arithmetic operations in the binary system. In ES2, we could generally use study materials of any scientific subject, and those would be adequately modified to suit the needs of the system ES2.

For the system ES2 simulation, the same numeral values are used as an input for the expert system ES1 (Table 4). The expert system ES2 derives assessment of all 16 linguistic values of output variable VERSION (version of study materials) with regard to individual persons of students from experiments 1 and 2. For simulating experiments, particular input values are mentioned in Table 4, in Table 6 there are values of the output variable ascribed and derived by the expert system ES2.

Experiment no	1						2				
Suitability assessment	0,53	0,47	0,40	0,40	0,33	0,27	0,6	0,4	0,33	0,27	0,13
Order recommended	1	2	3	4	5	6	1	2	3	4	5
Recommended versions	V9	V10	V11	V12	V1, V2, V3, V4	V5, V6, V7, V8, V13, V14	V8	V6	V14, V16	V5, V7, V13 V15	V1, V2, V3, V4, V9, V10, V11, V12

Tab. 6: Order of study materials recommended by the system ES2

Experiment 1 chooses study materials for the reflexive, verbal and holistic student (Table 5). The system thus correctly designated the version V9 as the most suitable material (Table 6). Remaining versions of study materials have lower ascribed values, the student can also utilize versions V10, V11 and V12 for his/her knowledge completion (the value of these materials is 0,4 or higher), remaining versions of materials are rather irrelevant for the student of this type.

Experiment 2 designates study materials for the student who is rather active, visual and a perfectionist (Table 5). The system ES2 correctly recommends the version V8 as the most suitable material (Table 6). The student can utilize the version V6 as well to complete his/her knowledge (but the value of this version is lower).

The Adaptive Loop AS1

Modification of recommended study materials for the following learning cycle has two options:

a) we assume that the result of the evaluative test KNOWLEDGE TEST (Fig. 1) will be the knowledge evaluation of three studied chapters in

$$k_1 = 3$$
$$k_2 = 1$$
$$k_3 = 2$$

The result means that the chapter k_1 subject matter has been mastered, the subject matter of chapters k_2 and k_3 needs to be revisited in the following learning cycle. That is why the chapter k_1 is eliminated from the study materials recommendation for the following learning cycle.

b) after the preceding learning cycle, if the student ratiocinates that s/he did not estimated his/her study characteristics correctly, s/he can use the offer of filling in the questionnaire PERSONAL QUESTIONNAIRE once again (Fig. 1). That would start the process of a new cycle of both the expert system ES1 and ES2 as well as recommending new and modified versions according to the new expert system ES1 result.

The Adaptive Loop AS2

We may assume that the expert system ES2 recommends the student a relevant study material V1. It means that during derivation the dominant rule was the rule RB (5) which has full weight (WRB = 1) in its initiative base of the expert system ES2

$$\begin{aligned}&RB: IF(SVisGRA) and (ZZIisTEO) and (SAisINT) and (PUisHOL)\\&THEN(VERZEisV1)\\&W_{RB}=1\end{aligned} \tag{5}$$

But the student marks the version V2 as the subjectively relevant material (from which s/he studied successfully) in the output questionnaire QUESTIONNAIRE. Consequently, a new rule RA will be added to the knowledge base of the system ES2 (6)

$$\begin{aligned}&RA: IF(SVisGRA) and (ZZIisTEO) and (SAisINT) and (PUisHOL)\\&THEN(VERZEisV2)\\&W_{RA}=0{,}5\end{aligned} \tag{6}$$

Dynamics of (learning process) knowledge base ES2 modification is retained via rule balance W_{RA}, $W_{RB} \in$ <0,1>. If it is the case of first modification occurrence, the new rule *RA* will be ascribed lower weight W_{RA} = 0,5. If the same modification *appears* in another student's questionnaire, the rule *RA* weight will be improved to $W_{RA} = W_{RA} + \Delta$ and the original rule *RB* will be improved to $W_{RB} = W_{RB} - \Delta$. If the rule *RA* occurs again, the process will be continued till full weight W_{RA} = 1 is reached and the original rule *RB* will be kept in the base with lowered weight W_{RB} = 0,25.

That formalizes the importance of new rule *RA* dynamics in the learning process of the model ES2.

Conclusion

Current pedagogical research has striven to create an adaptive computer educational system which would come closest to each student's needs and skills, and would ensure the quickest and the most effective way of acquiring the necessary knowledge in the field concerned. Modern informational technologies are fundamental which make use of unconventional methods of artificial intelligence to mechanically and abstractedly formalize mental models of experienced educators, which leads to mechanical representation of their sophisticated teaching methods and procedures.

The structure of the adaptive educational system ADEPT presented includes two on-line fuzzy-logic expert systems. Both expert systems formalize mental decision-making functions of an experienced educator via computer. The first system is dedicated to deciding about the student's study type, the second is dedicated to deciding about recommended structure of a study material for a student of a particular study type. Furthermore, the ADEPT system contains two adaptive tasks. The first adaptive task deals with the issue of continuous modification of the recommended study material on the basis of study results in individual learning cycles. The second adaptive task deals with the issue of continuous knowledge base studying of the expert system for recommending the study material according to the information about the student's possibly modified learning procedure.

The ADEPT system is implemented in developing environments LFLC and MATLAB. Simulating tasks which were carried out show the results of both expert systems' decision-making functions applied to two different study types of users. Simulations results confirm correctness of their function. Functions of both adaptive loops are also introduced via simulations.

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