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ADAPTIVE METHOD FOR PERSONALIZATION OF LEARNING UNITS

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1 INTRODUCTION

1.1 Relevance of the study

Using information technologies for education increases the quality and efficiency of learning, and improves learner's and teacher's work. Contemporary education is unimaginable without information technologies and utilizing their facilities. Learning objects and learning units are the examples of those possibilities. However, only a partially qualitative effect could be obtained not applying personalization of those components of e-learning and thus finding personalized learning paths in learning units.

The main principle of personalized learning states that there is no unique single learning strategy suitable for all learners, and therefore a successful achievement of learning aims depends, for the most part, on the fact how individual learners' differences are taken into consideration in teaching and learning process. Many authors stress that personalized learning improves learners' achievements and increases learning efficiency. Personalization can be put into practice from two perspectives, namely, teachers' and learners'. Looking from the teachers' perspective, personalized learning is realized on the basis of teachers' experience and intuition. However, this kind of personalization will not always be equally efficient with respect to learners.

In e-learning, personalization is capacitated by designing and developing adaptive and intelligent systems. The target of these systems is to improve learning. Contemporary learning systems strive to incorporate analysis of historical data about the previous users of the system by modelling learning process from the learners' viewpoint, and, thus, be able to adapt to a rapidly changing environment by providing learners not only accurate and high-quality learning material, but also taking into account the individual learner' s needs.

This research work is aimed to solve the problem of personalization of learning units paying a particular attention to finding personalized learning paths in learning units. The finding is based on learners' needs in terms of their learning styles.

Personalization can be seen from different perspectives, namely, when only one learning object or a learning unit is selected, and when a set of them is composed, i.e. personalization of a learning unit by finding suitable learning path. The former perspective formulates a learning object selection problem, while the latter solves a curriculum sequencing problem. However, while solving both problems, the main quite significant and integrated problem arises, i.e., how to efficiently match learning objects with particular learner's needs. One of the approaches used to perform the curriculum sequencing is named Social Sequencing. It is based on Swarm Intelligence methods. Based on literature overview, some of these methods have been applied to solve the aforementioned problem, but it has been noticed that a learning unit was personalized while it was considered as a static object so far. Meanwhile, in the real world a learning unit is a dynamic object, and it can be modified during learning process by inserting, deleting, and editing learning objects, activities, etc.

In the thesis, an adaptive method for personalizing learning units is proposed. The method is based on Ant Colony Optimization (ACO) and its application in the e-learning context, as well as its extension aiming to select the optimal learning paths for learners according to their learning styles addressing both static and dynamic learning unit. The research is focused on creating a new method for personalizing learning units in order to achieve better learning quality and efficiency.

1.2 Research object

The research object of this work is learning units and their personalization.

1.3 Aim and objectives

The aim of the thesis is to propose an adaptive method for personalization of learning units by selecting learning paths for learners according to their learning styles, and thus improving their learning results and saving learning time.

The objectives of the thesis are as follows:

1. To explore the e-learning components (learning objects, activities, environments, learning units) and technological peculiarities of personalized e-learning (functions of adaptive systems, properties of the components used in them).
2. To analyze existing approaches and methods applicable for personalization of learning units.
3. To develop an adaptive method for personalization of learning units based on the applying Ant Colony Optimization by selecting optimal learning paths for learners according to their learning styles in both static and dynamic learning units.
4. To perform an experimental approbation of the method developed.

1.4 Research methods

In the thesis, various research methods were used, i.e., an analysis of scientific literature, mathematical modelling, computer simulations, empirical experiment, and statistical analysis of its results. Descriptive statistics and *t-test* statistical analysis for two independent samples have been used to analyse the data of the research.

1.5 Scientific novelty

1. The adaptive method is proposed for personalization of learning units by selecting optimal learning paths for learners according to their learning styles addressing both static and dynamic learning units.
2. Ant Colony Optimization has been modified in order to apply Ant Colony Optimization to the e-learning context, as well as to extend it to selecting optimal learning paths for learners according to their learning styles addressing both static and dynamic learning units. Although the parameters and functions used in this work are the same as defined in original Ant Colony Optimization, there are two novel extensions as follows:
   a) A learner’s profile is modelled as a multiple criteria set B = LSt({w1, w2, w3, w4}), where {w1, w2, w3, w4} are the values of learning style according to the chosen typology of learning styles.
   b) In this work, contrary to other research works, personalized learning units are considered not only as static objects, but also as dynamic ones. Therefore, in order to achieve more effective personalization of learning unit, a novel modification strategy based on “new component” pheromone integration has been proposed.

1.6 Practical significance

The results of an empirical experiment have shown that learning in the e-learning system applying the method proposed improves learners' learning results and saves their learning time. This fact indicates that the developed adaptive method for personalizing learning units is practically applicable in e-learning, and enhances the learning quality and efficiency.

The proposed approach is important for tutors by helping them to monitor, refine, and improve learning units, learning modules, and courses.

1.7 Statements defended

1. Ant Colony Optimization is applicable for personalization of learning units by finding personalized learning paths for learners according to their learning styles addressing both static and dynamic learning units.
2. The proposed adaptive method for personalization of learning units improves learning results and saves learning time.

1.8 Approbation and publications of the research

The main results of the thesis were published in 14 scientific papers: 8 articles in periodical scientific journals, and 6 papers in the proceedings of scientific conferences. The main results of the work have been presented and discussed at 15 national and international conferences.

1.9 Structure of the dissertation

The dissertation consists of the terms and abbreviations section, four chapters, general conclusions and results, list of references and appendices. The work includes 138 pages of text, 39 figures, 6 tables and 7 appendices. The dissertation is written in Lithuanian.

2 PERSONALIZATION IN ADAPTIVE E- LEARNING SYSTEMS

2.1 Components of e-learning

Based on literature overview, e-learning is examined from different perspectives, respectively, distinguishing its various components. In 1980, Keegan (1980) identified six main e-learning components which are generalized in the research of Targamadzė (2010) into three ones: 1) physical distance between a teacher and a learner, 2) technology (pedagogical and technical) requirements, 3) necessity of interaction among participants. Henry (2001) distinguishes three e-learning components: content, information technology, and services. Štuikys & Brauklytė (2009) state that e-learning consists of three essential components: learning objectives, teaching content, and learning activities. Dietinger (2003) divides e-learning components into four components: 1) one or more learners; 2) interactive multimedia content; 3) program-learning environment; 4) one or more teacher assisting the learners.

The analysis of literature indicates that one of the key e-learning elements is learning material that is identified as a learning object (LO). The layout structure of LOs usually describes a teaching strategy of a teacher which is not necessarily coincident with the learner's learning strategy. Moreover, differently arranged LOs change the method of teaching and learning. Looking at the pedagogical model from a technological standpoint, a learning design specification is developed, which is referenced as IMS LD (2003) in the e-learning context, and it is intended to describe the whole pedagogical model in a formal manner. Under this standard, a learning unit is referred to as an aggregation of learning activities that takes place in a particular learning environment using particular LOs.

The rapid development of e-learning increases the studies of e-learning systems, the main objective of which is to make learning more efficient (Brusilovsky & Peylo, 2003; Graf, 2007; Mulwa, Lawless, Sharp, Arnedillo-Sanchez, & Wade, 2010). Currently, there are a lot of e-learning systems but all of them can be divided into four main groups (Kavcic, 2004; Kelly & Tangney, 2006; Koper & Tattersall, 2004; N. Manouselis, Drachsler, H., Vuorikari, R., Hummel, H. G. K., & Koper, R., 2009), namely, course management systems, adaptive hypermedia educational systems, intelligent tutoring systems, and learning networks. The examination results of the components of these systems and their functions (Table 2.1) shows that, according to Graf (2007), adaptive systems are rarely used in the real learning situations due to the following reasons:

1. The systems are designed for specific content or special activities, e.g. accounting, learning mathematics, adaptive tests, and surveys.
2. The learning content may not be re-used since it is related with adaptation strategies.
3. Great efforts are needed for a course designer to prepare a course, e.g. to develop a domain ontology.
4. They are grounded on specific user's and domain models.

Table 2.1. Components of adaptive e-learning systems (Henze & Nejdl, 2004)

Component	Function
Domain model	Describes learning resources, their metadata and a set of domain knowledge (e.g. domain ontology).
User model	Describes individual users (user groups), and user characteristics, as well as rules for expressing whether a characteristic applies to a user.
Observation model	Describes observations of related users, documents/topics.
Adaptive model	Comprises the rules for describing adaptive functionality.

The evolution of e-learning systems shows that the main challenge for contemporary e-learning designers is to design and develop highly flexible, learner-centred and evolving from the bottom upwards systems, where each user is allowed to add, edit, delete, or evaluate learning resources at any time. Therefore, an increasing attention is paid to the research of integral adaptive intelligent components which possess adaptive properties preservation in a changing context.

2.2 Peculiarities of e-learning personalization

The overview of literature shows that there is no concrete definition of personalization so far. The main idea is to achieve an abstract common goal, i.e. to provide users with what they want or need without expecting them to ask for it explicitly (Mulvenna, Anand, & Büchner, 2000). Since it is a multi-dimensional and complicated area (also covering recommendation systems, customization, adaptive Web sites, Artificial Intelligence), a universal definition that would cover all its theoretical and technological areas has not been proposed so far (Germanakos, 2005). From the educational viewpoint, personalization attempts to provide an individual with tailored products, services, information, etc. A more technical standpoint to personalisation is linked with the modelling of Web objects (products and pages) and subjects (users), and their categorization, organizing them to achieve the desired personalization.

The main principle of personalized learning states that there is no single unique teaching strategy suitable for all learners, and mostly successful achievement of learning objectives depends on how teaching and learning are adapted according to learners' differences. Thus, personalization can be realized from two perspectives, namely, the user (Essalmi, Ayed, Jemni, Kinshuk, & Graf, 2010) and used technologies (Anand & Mobasher, 2005). Looking at the personalization from the user's viewpoint, personalization is treated as the best choice of a teaching alternative according to individual learners' skills, e.g. by recommending learning paths through LOs according to a learner's level of knowledge, by hiding some LOs with regard to the learner's performed tasks, etc. (Popescu, 2010). In this case, the basic goals of personalization are to maximize learner's satisfaction of teaching and learning process, to minimize learning time (to faster achieving learning objectives) and pedagogical efficiency (time cost minimization by monitoring the course). Thus, the personalized learning approach promotes a tailored support system helping a learner to learn. In order to personalize learning, one needs to personalize LOs, learning activities, learning environments, etc. Adaptive learning used in hypermedia systems has been discussed from quite different perspectives. The main approaches are adaptive curriculum sequencing, adaptive presentation, and adaptive navigation support. In the adaptive curriculum sequencing, the learner is provided with the most suitable individually planned sequence of learning objects to learn from, and a sequence of learning tasks to work with, i.e., this technology can help learners to find the most suitable learning path through the learning material (Al-Muhaideb & El Menai, 2011).

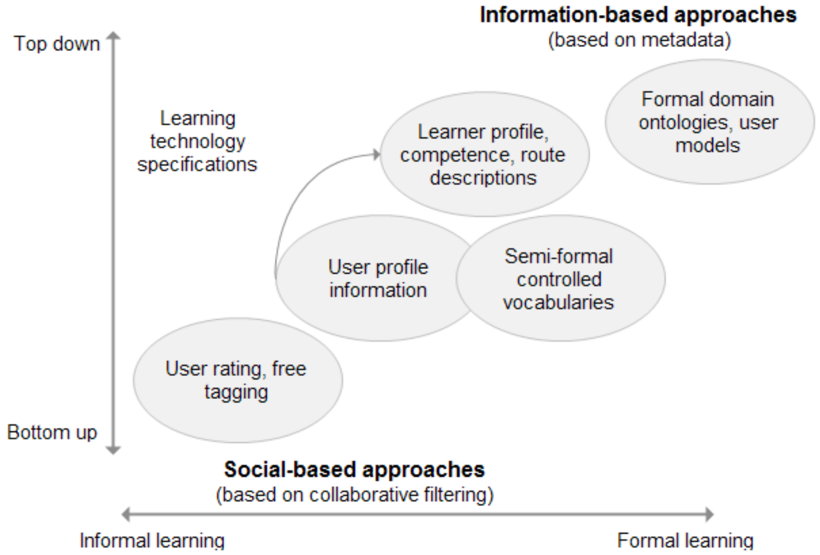

Fig. 2.1. Classification of personalization methods (Hummel, Van Den Berg et al. 2007)

The review of literature shows that personalized learning is more effective than "nonpersonalized", and looking at it from the technological aspect, it can be implemented by designing and developing adaptive intelligent e-learning systems or integral components for non-adaptive systems, e.g. course management systems. In the work, it was found that different approaches to e-learning personalization were applied so far. Hummel et al. (2007) classify personalization methods into two groups (Fig. 2.1.): 1) Information-based approaches – they comprise learning technology standardization, metadata, and application of a semantic web and 2) social-based approaches – usually data mining, collaborative filtering methods, etc.

2.3 Approaches used for personalization of learning units

Personalization of learning units is not a new idea. In order to implement it, different approaches are used (for instance, soft ontology (Karampiperis & Sampson, 2005), genetic algorithms (Chen, 2008), multiple-criteria analysis (N. Manouselis & Sampson, 2002)), etc. Personalization can be seen from two different perspectives, namely, while only one LO or a learning unit is selected, and while a set of them is composed, i.e. personalization of a learning unit by finding a learning path. The former perspective formulates LO selection problem, and the latter one solves curriculum sequencing problem. However, while solving both problems the significant and integrated problem of efficiently matching LOs to a learner's needs according to his/her features has arised. The full survey carried out by Al-Muhaideb & Menai (2011) presents and discusses two approaches which can be used to fulfil the curriculum sequencing, depending on whether the solution incorporates experiences of other similar learners, called Social Sequencing, or it is based mainly on the individual learner, called Individual Sequencing. According to Al-Muhaideb & Menai (2011), Swarm intelligence methods like ACO and Particle Swarm optimization are the most promising Social Sequencing methods, while genetic algorithms and Memetic algorithms are the most often used Individual Sequencing methods. The Social sequencing approach does not take into account the individual characteristics of both the learner and the learning resources. The choice of the optimal curriculum sequence is based on the collective path and performance of the entire learners' society.

Several researchers are found which deal with the selection of personalized learning paths dependent on learning styles and use of the social sequencing approach to attain the selection. In the Wang, Wang, & Huang (2008) work, the selection of a set of LOs is based on learners' preferences grouped in four "homogeneous" categories, and the selection of LOs is performed. Other authors Yang & Wu (2009) use the notion of the "attribute" by describing each learner as an ant which has one of the Kolb's learning style types. The main drawback in their work is formation of a non-realistic suitability function. Moreover, that function relies on the rule-based approach which, according to Gao, Liu, & Wu (2010), is not flexible and not really personalized. With reference to the analysis of some literature resources, one could note that researchers have not considered the importance of the proportion values of different learning styles. Moreover, so far, the personalization of learning unit using this technique was explored while a learning unit is considered as a static object; meanwhile, in the real world, a learning unit is a dynamic object, and it can be modified during learning process by inserting, deleting, and editing LOs, learning activities, etc.

The basic philosophy of the ACO algorithm is as follows: a colony of ants move through different nodes, and their movement decision is influenced by trails and attractiveness, i.e. each ant gradually constructs a solution to the problem by depositing the pheromone information. This pheromone information will direct the search for following ants. Furthermore, the algorithm also includes trail evaporation (it reduces all the trail values over time thereby avoiding any possibilities of getting stuck in local optima) and local search actions (they are used to bias the search process from a non-local perspective).

3 ADAPTIVE METHOD FOR PERSONALIZATION OF LEARNING UNITS

The aim of this work is to propose an adaptive method for personalization of learning unit by selecting learning paths for learners according to their learning styles, by improving their learning results and saving learning time. The method comprises a set of applied assumptions, requirements, and functions, and is based on ACO. This method is the application and extension of ACO. Although the parameters and functions used in this work are the same as at defined in ACO, there are two extensions, namely, an extended model of learning style and an approach to personalization of learning unit by selecting optimal learning paths for learners according to their learning styles addressing both a static and dynamic learning unit. According to the aforementioned extensions, heuristic information, pheromone update, and local search functions are modified. The main idea of this method is that the paths of pheromones are updated for different learning styles in order to create LOs recommendations based on learning styles.

3.1 Assumptions for developing a method

While developing a method, some requirements are needed:

1. The information about a learner's learning style should be known.
2. Learning unit should be actively attended by many learners.
3. Structure of learning unit is formed by a tutor keeping in mind the time allotted.
4. Learning unit should consist of LOs and their alternatives for the same topic.

3.1.1 Structure of a learning unit

The learning process as an engineering object can be considered as a life cycle of creation and existence of knowledge. Within this cycle, the learner can navigate through learning unit, come back and re-analyse the content if there are problems, and to improve his/her knowledge, as well as to continue his/her learning till achieving the planned learning goals. Learning unit can be decomposed into time slots containing the learning content presented as a particular learning path. In this case, navigation is possible through all LOs in all the corresponding time slots. Learning unit is presented as a completely connected graph $G_V = (V,L)$, the nodes of which are components V, and the set L fully connects the components V. G_V is called a construction graph, and the elements of L are called as connections or *arcs* (r,s), $r,s \in L$. (Fig. 3.1.)

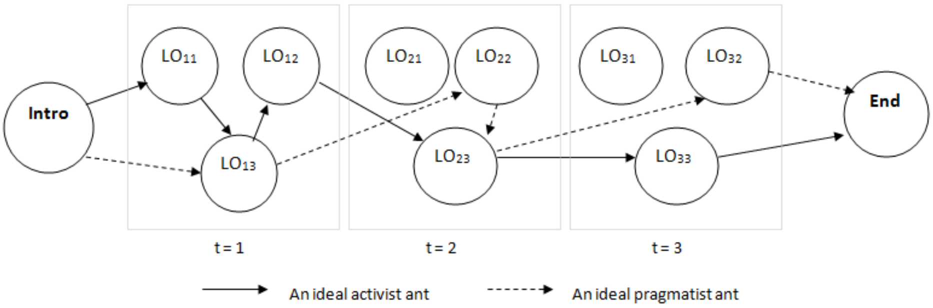

Fig. 3.1. Structure of a learning unit

Each LO and a learner's profile are parameterized. However, contrary to the description using metadata standards (IEEE LOM (2002) or content specifications such as IMS LD (2003)), they are described by information on LOs where it is collected from learners' activities in log files. Information on LO usage accumulated in log files is then exploited with a view to make decisions about their suitability for a particular learner. On this basis the learning material is characterized by two types of variables, i.e. qualitative and quantitative measurements. Qualitative measurements are meant as e.g. learning results, and quantitative – time, number of visits in LOs, etc.

3.1.2 Learner's profile

A learner's profile is drawn up and described by one of the learners' models, presented in the references, i.e. a stereotyped model. According to this model, learners are attributed to the categories, and then the system automatically adapts its mode depending on the category the learner belongs to. A learner is assumed to aim at a specific target T (e.g. pass a test, exam, etc.), which, in particular, depends on his/her learning style. Then the target T is defined as $T=\{LSt\}$. In contrary to other researchers' work, the learning style of a learner is modelled as a multiple criteria set $B = LSt(\{w1, w2, w3, w4\})$, where $\{w1, w2, w3, w4\}$ are the values of learner's learning style according to chosen typology of learning styles, e.g. Honey and Mumford (1992). It means that each learner is modelled as a weight set, and each learner may leave up to 4 different pheromone traces on his/her learning path and react, respectively, to 4 types of pheromones.

3.2 Statement of the problem

In order to create a method for personalizing learning units that enables adaptive learning paths according to learning styles, and improves their learning results as well as saves learning time, ACO is modified as follows:

1. In order to personalize a learning unit according to learning style, an extension of ACO is proposed by introducing a multiple criteria model of a learning style.
2. In order to apply ACO in the e-learning context, its modification and extension for personalizing both a static and dynamic learning unit were introduced. In the thesis, insertion of only new learning objects was investigated.

The assumption is used that each learners group having similar learning styles distinguishes specific learning paths. Further, the following elements are formally defined: learning unit, learning path, dynamic learning unit, learner, learning results, and learning time, and optimization problem.

<u>Learning unit</u> – $LU_T (LO_{ij})$, $i=1,\dots, n, j=1,\dots m$, as completely connected graph $G (V, L)$, V, is the number of nodes (considered as LOs), and L is the number of connections (considered as part of the learning path (LP)). There are two nodes V_p and V_g (V_p, V_g) that are treated as initial and final nodes, where V_p and V_g are LOs.

<u>Learner</u> – $B = LSt(\{w1, w2, w3, w4\})$, where $\{w1, w2, w3, w4\}$ are the values of the learning style.

<u>Learning results of a Learner</u> – BL_R.

<u>Learning time of a Learner</u> – BL_{TR}.

<u>Learning path</u> – a set $LP (V_p, LO_{11}, \dots, LO_{nm},V_g)$, where LO_{ij} is LO is chosen by a concrete learner, $i=1,\dots, n, j=1,\dots m$.

Dynamic learning unit – learning unit that changes over time, i.e. it can be modified during the learning process by inserting, deleting, and editing LOs.
Optimization problem – to find such a learning path LP_{opt} from the node V_p to the node V_g, that satisfies the following conditions:

1. $min\ BL_{TR}$ (to minimize the learning time of a learner),
2. $max\ BL_R$ (to maximize the learning results of a learner).

3.3 Adaptive method for personalization of learning units

In order to solve the problem described in section 3.2, modified and extended part of ACO is presented in Fig. 3.2., i.e. heuristic information settings, global pheromone update strategy, and local search strategy modifications.

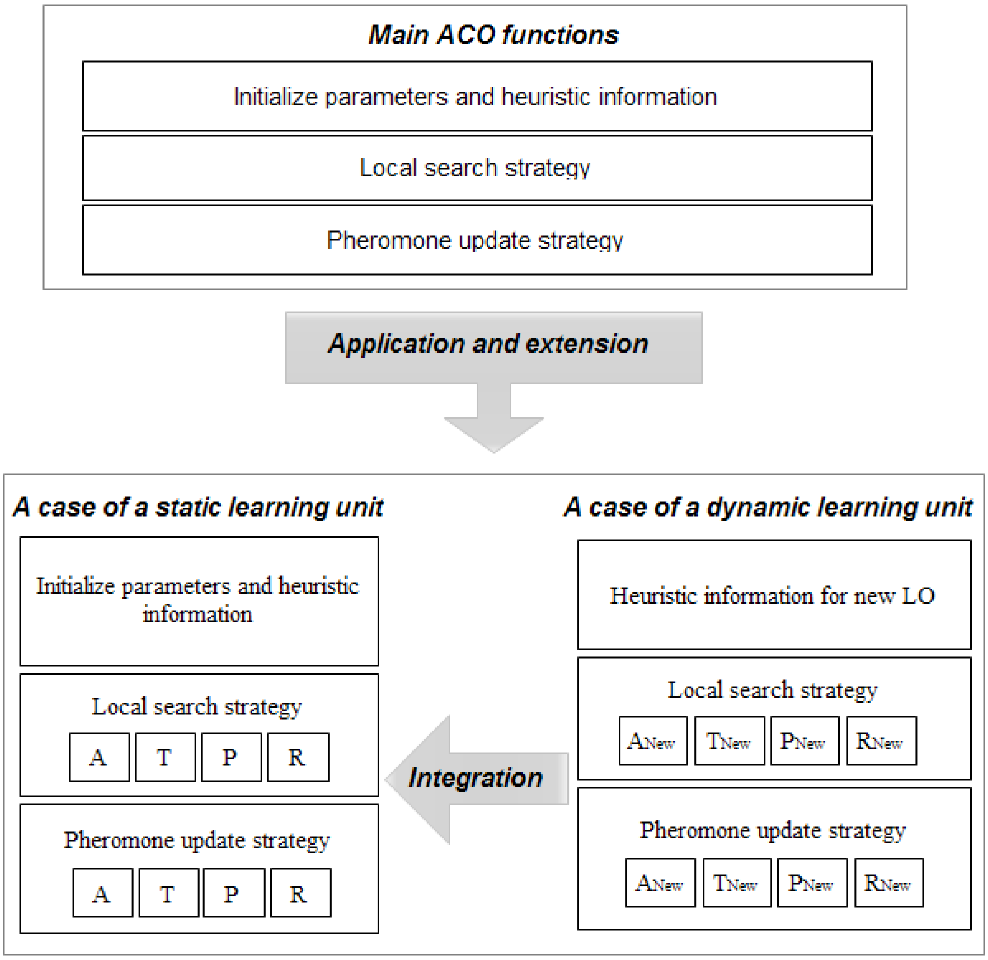

Fig. 3.2. Schema of modified and extended ACO

Notations used in the method are as follows: α is a relative importance of the pheromone, β is relative importance of the heuristic, τ_{rs} is a pheromone located on *arcs (r,s)*, γ is relative importance of the "new component" pheromone, ρ is an evaporation rate, ρ_{new} is an evaporation rate for a "new component", η is heuristic information, q is a random number uniformly distributed in interval [0, 1], $q_0 \in [0, 1]$ is a parameter that determines the relative importance of exploitation versus exploration, $N_k(n)$ denoted a set of nodes that remain to be travelled by ant k on node n, S is a learner's learning result, w_l is values of learning styles, and ψ_{rs} is a "new component" pheromone located on *arcs (r,s)*.

Modification of heuristic information settings

Heuristic information η_{rs} is expressed as the conscious intensity of learning from the rth node to the next sth node and is defined as follows:

$$\eta_{rs} = \frac{1}{e^{|\Delta t|}} \quad (1)$$

where Δt is a time unit difference between the *r*th node to the next *s*th node. The heuristic information provided by time slots defines the appropriate selection probability of another learning object, which is arranged in *arc(r, s)* with the value defined in formula (1). The exponential function was chosen in order to promote a consistent gradual transition from one to the next time slot, i.e. from the first topic to the second one, from the second to the third one, but not from the first to e.g. twelfth, etc.

Modification of the global pheromone update strategy

a. The case of a static learning unit

$$\begin{aligned}
&\forall l,\ w_l \ - \ learning\ \ style,\ l = 1,...,4.\\
&1)\ \ if\ \ rs\ \ \in passed\ \ path\ \ and\\
&if\ \ S \geq S_{good\ grade},\ \ \tau_{rs}{}^{l}(t) = \rho\tau_{rs}{}^{l}(t-1) + w_l \Delta S,\\
&\Delta S = S - S_{good\ grade}\\
&2)\ in\ \ another\ \ case\ \tau_{rs}{}^{l}(t) = \rho\tau_{rs}{}^{l}(t-1)
\end{aligned} \quad (2)$$

b. The case of a dynamic learning unit

$$\begin{aligned}
&\forall l,\ w_l \ - \ learning\ \ style,\ l = 1,...,4.\\
&1)\ \ if\ \ rs\ \ \in passed\ \ path\ \ and\\
&if\ \ S \geq S_{good\ grade},\ \ \tau_{rs}{}^{l}(t) = \rho\tau_{rs}{}^{l}(t-1) + w_l \Delta S,\\
&\Delta S = S - S_{good\ grade}\\
&2)\ \ else\ \ \tau_{rs}{}^{l}(t) = \rho\tau_{rs}{}^{l}(t-1)\\
&3)\ \ on\ the\ \ passed\ \ path,\ \ \psi_{rs}{}^{l}(t) = \psi_{rs}{}^{l}(t-1) - (1-\rho_{new\ component})w_l\psi_{rs}{}^{l}(t-1).
\end{aligned} \quad (3)$$

In the proposed method, there are three extra conditions:

1. An ant (representing a learner) will leave a certain amount of pheromones only if after finishing its learning path it gets a very good grade $S > S_{good\ grade}$. It is reasonable to do that in order to get qualitative pheromones from an ant. That helps to prevent the accumulation of pheromones in the paths generating bad results.
2. $S_{good\ grade}$ can be defined by a tutor.
3. Each ant leaves a pheromone according to its learning style preferences and results by condition No.1.

As a result, the modified pheromone updating rule that includes evaporated pheromones and the amount of pheromones the ant *k* deposits on the *arcs* it has visited, multiplied by the ant's learning style type proportion value, is defined as in (2) and (3).

Modification of the local search strategy

At each decision step, the ant k applies the probabilistic action choice rule to decide which node to visit next. According to the proposed method, modified rules (4) and (5) are as follows: ant k at the node n selects the next node s to move to, if $q \leq q_0$

$$p_{ns}^{k} = \begin{cases} 1, & if \quad s = \arg\max\limits_{u \in N_k(n)} \left\{ \sum_{l=1}^{4} (\alpha w_l \cdot \tau_{nu}^{l} + \gamma w_l \psi_{nu}^{l}) + \beta \eta_{nu} \right\} \\ 0, & \end{cases} \tag{4}$$

or else

$$p_{ns}^{k} = \frac{\sum_{l=1}^{4} (\alpha w_l \cdot \tau_{ns}^{l} + \gamma w_l \psi_{ns}^{l}) + \beta \eta_{ns}}{\sum_{\mu \in N_n^k} \left(\sum_{l=1}^{4} (\alpha w_l \cdot \tau_{nu}^{l} + \gamma w_l \psi_{nu}^{l}) + \beta \eta_{nu} \right)}, \quad jei \;\; s \in N_k(n) \tag{5}$$

ψ_{ns}, $\psi \in (0,1)$. ψ_{ns} is a "new component" pheromone introduced into the method to attract ants to a new or changed material. This would allow getting a fast feedback about the inserted LO and checking its suitability for a new optimal solution. The "new component" should be conformed with learning styles, since one does not knows the suitability of a new or edited material to learners. Thus, the "new component" pheromone is modelled in a way to attract a few ants of each learning style, and if the "new component" was useful, – a learner sets the learning style pheromone to mark the new optimal learning path. The application of the proposed method from a learner perspective is proposed in Fig. 3.3.

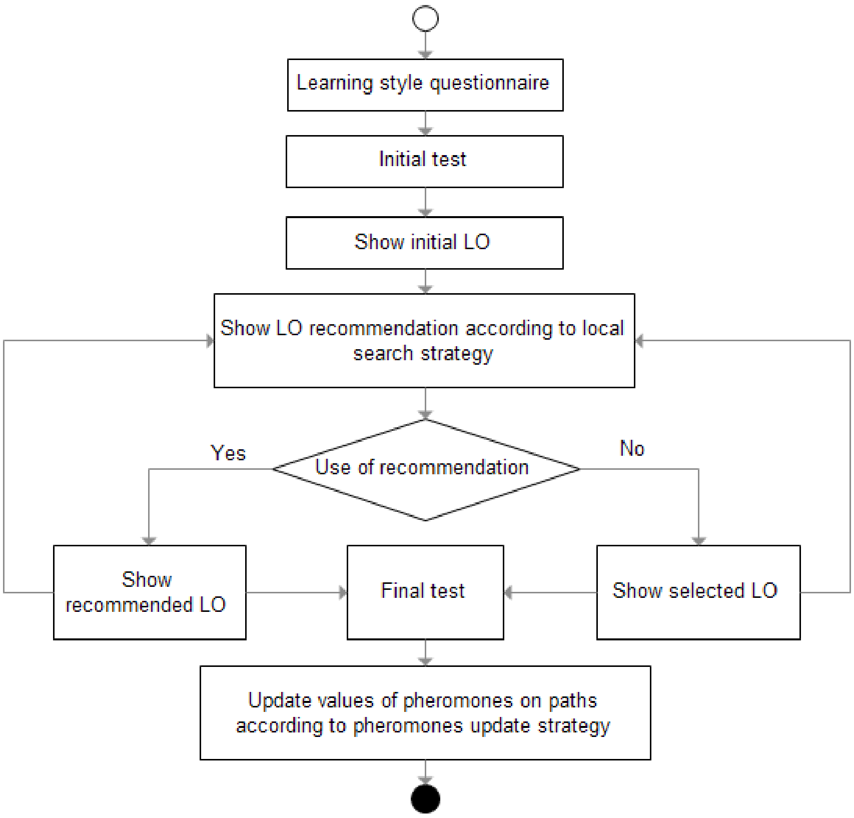

Fig. 3.3. The proposed method from a learner viewpoint

In order to investigate whether the proposed method allows us to create personalized learning path for learners in terms of learning styles, two computer simulations have been carried out.

3.4 Computer simulations and results

In order to show that modified ACO is applicable for personalization of learning units by finding personalized learning paths for learners according to their learning styles in case of a static learning unit computer simulation no.1 was performed.

The aim of this computer simulation was to confirm a part of the first defended statement. Computer simulation has showed that using the proposed method with the modified ACO personalizes learning paths according to learning styles, i.e. it finds a good enough solution and stabilizes it. The obtained results indicate that ACO can be used to personalize learning paths in a static learning unit. During the experiments, it was noticed that the efficiency of the proposed method depends on the parameter values. The parameter values optimization is out of the scope of this work. The parameter values have been obtained applying the trial and error method used in the experiment and defined as follows:

$\alpha = 0.7, \beta = 1.0, q_0 = 0.09, S_{good\ grade} = 0.7, \rho = 0.9.$

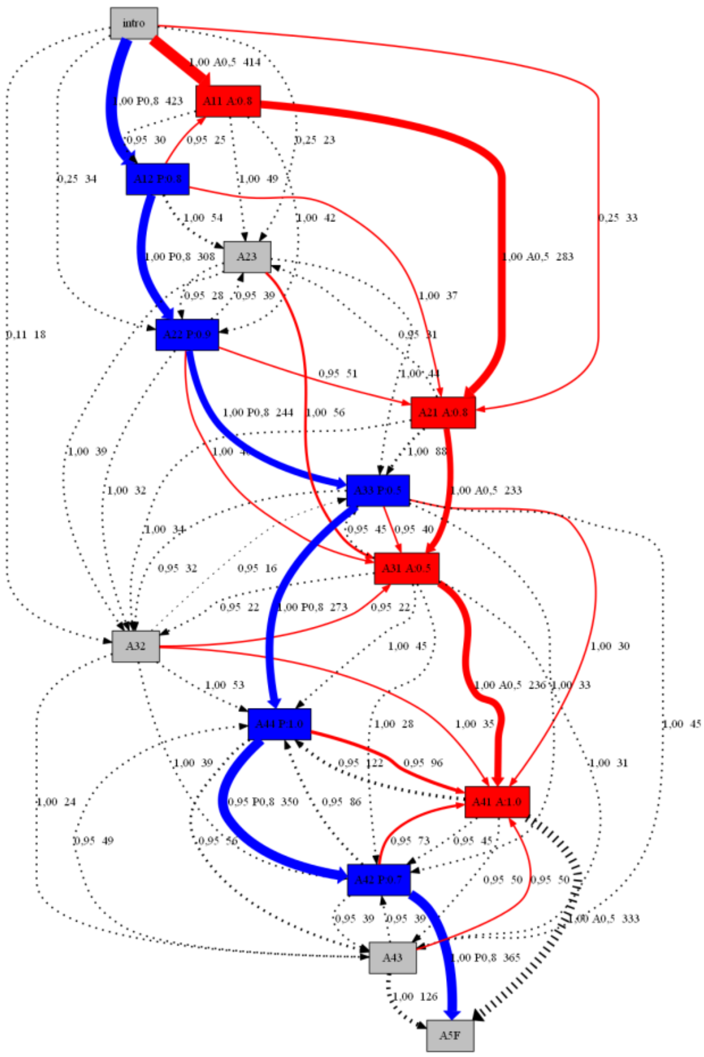

Fig. 3.4. An example of pheromone trace after virtual learners finished their paths

Simulation No.2. The aim of the second computer simulation was to confirm the first defended statement about the suitability of the proposed method for a dynamic learning unit. In order to examine the performance of the extended ACO and to validate it, new LOs are inserted. This experiment was conducted with the following values of parameters: $\alpha = 0.7, \beta = 1.0, q_0 = 0.09, S_{good\ grade} = 0.7, \rho = 0.9, \rho_{new\ component} = 0.8.$ It has been found that the extended ACO performs better (Fig. 3.5) with $\gamma \in [0.4,1]$. The simulation results reveal that, as $\gamma = 0$, i.e. the new LO is ignored, the quantity of iterations ranges around 100. If $\gamma \leq 0.2$, it takes more iterations to notice the new LO as the method performs a random search in a probabilistic way. By increasing the value of the parameter γ (the new LO is taken into account), the quantity of iterations is decreasing as $\gamma \in [0.4,1]$, the quantity of iterations stabilizes and decreases up to 30. If $\gamma > 1$, the proposed method does not solve the problem, i.e. the newly inserted LOs are playing too aggressive role and may spoil optimal paths. The relationship between the γ rate and the number of iterations needed to perform better is presented in Fig. 3.5.

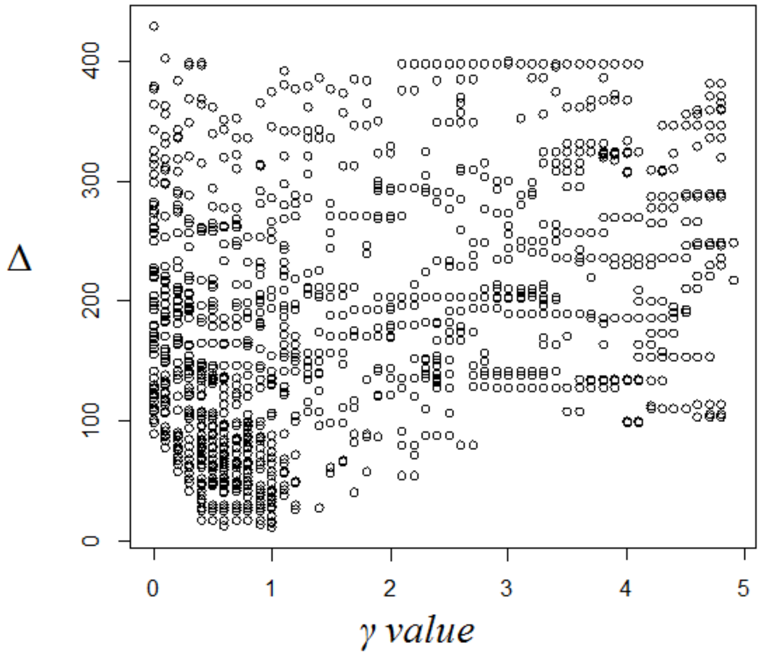

Fig. 3.5. Influence of values of the parameter γ on the ACO performance

4 EXPERIMENTAL APPROBATION AND RECOMMENDATIONS

4.1 Strategy of the experiment

The main goal of the empirical experiment is to investigate the usefulness of the proposed method for particular learners' learning. The experiment was done following the strategy of four stages, i.e. (1) search, preparation and evaluation of LOs, (2) adoption of the learning style questionnaire, implementation of the pilot study, (3) development of an e-learning system prototype with the proposed method, and (4) data collection and analysis of the results.

4.1.1 Search, preparation and evaluation of LOs

The learning material was prepared according to the basic general education programs for 8 and 9-year classes in the field of secondary school Mathematics for two topics "Linear Equations" and "Incomplete quadratic equations".[1]

4.1.2 Adoption of learning style questionnaire and implementation of the pilot study

In order to identify particular learners' learning styles, a shortened questionnaire for learning styles based on Honey (1992) work[2] was adopted, and correspondent pilot study was implemented. This study was aimed to investigate the suitability of the adopted questionnaire to find out whether there is a statistically significant difference among learning activities of learners with different learning styles. The results obtained show that there is a statistically significant difference among learning activities of three learners' groups with different learning styles regardless of the document type of learning material (Fig. 4.1.). It means that a number of factors affect learning and learning style is one of them.

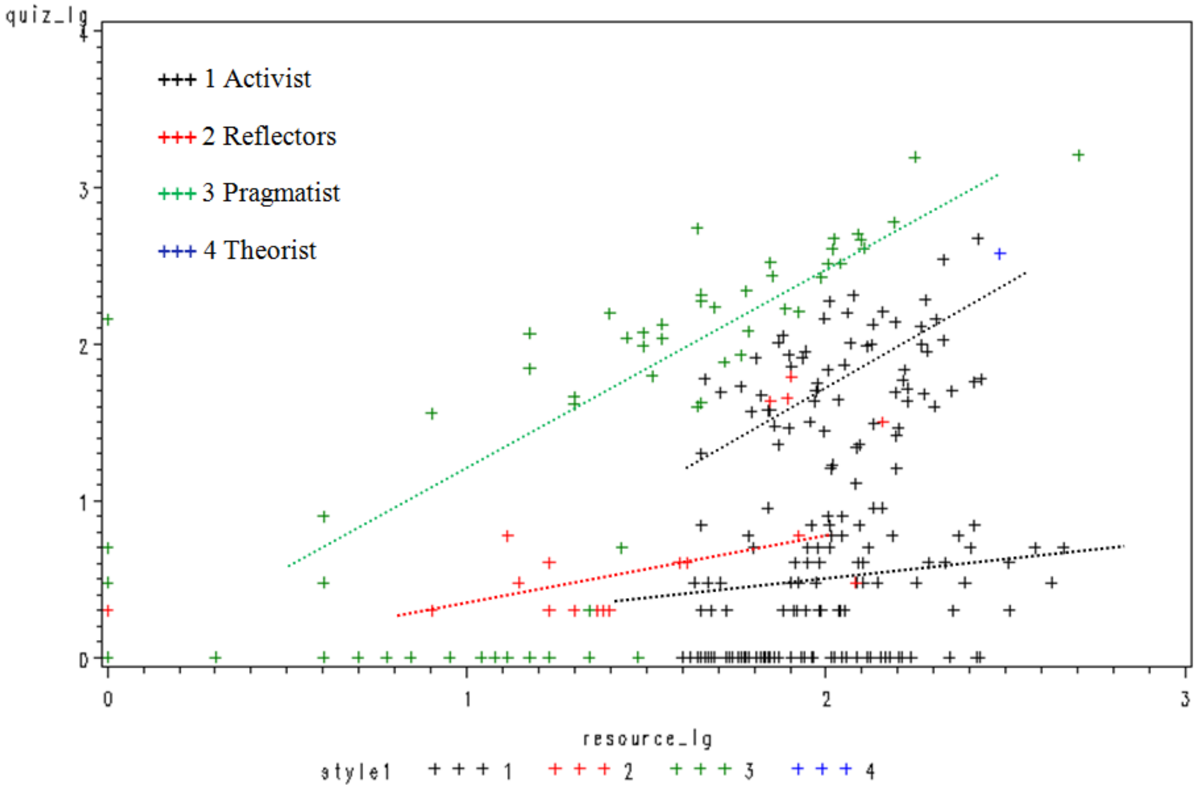

Fig. 4.1. Distribution of learning styles according to learners' learning activities

4.1.3 Development of e-learning system prototype

Two different versions were developed of the system and planned to divide the learners in each course into two groups, respectively. Each group was introduced into a particular version of the system. The first version of the system was developed without application of the method proposed. At the beginning this system had no data for

[1] http://portalas.emokykla.lt/bup/Puslapiai/pagrindinis_ugdymas_matematika_bendrosios_nuostatos.aspx
[2] http://www.peterhoney.com/eshop_product.aspx?pid=1015

recommendations, and, therefore, the system collected the data only and did not have any impact on particular learners' learning. The second version of the system was developed applying the method proposed, and its purpose was to provide LOs recommendations for learners. Adaptive link guidance is a non-aggressive personalization strategy that does not force users to follow a specific learning path through the content, but informs them about better options at every step, and, therefore, learners can choose LOs on their own. Although there are two versions of the system, their interfaces are identical. It has been done to prevent any influence of different user interface elements on learners' work with the systems. The number of learners working with each version of the system was as follows: 88 learners in the first version of the system, and 531 learners in the second version of the system.

Fig. 4.2 summarizes the differences between the two versions of the system and visualizes the direction of the expected effects that these differences will have. The main goal of this study is to show that the adaptive recommendations based on the method proposed improves particular learners' learning (i.e. improves learning results and saves learning time). Learners using the second version of the system were expected to outperform that using the first version ("v.1 < v.2" on Fig. 4.2.).

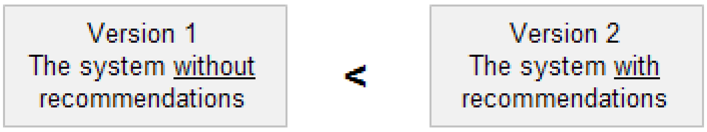

Fig. 4.2. Two versions of the system and the expected effects

A prototype of the e-learning system was designed and developed using Java. Its application is designed as web application and runs using any browser. The main functions for the end user are login, questionnaire for defining learning style, menu to navigate learning material, clear visualization of recommendations, and initial and final tests to estimate knowledge (Fig. 4.3.) Recommendations in the system are displayed in a non-aggressive way by highlighting a link to the next learning object recommended by the system.

The workflow of the learner comprises seven following steps: 1) registration to the system; 2) filling the learning style questionnaire; 3) pre-test; 4) learning of the topic "Linear Equations"; 5) learning of the topic "Incomplete quadratic equations"; 6) post-test; and 7) final work with the system.

A new learner logs into the system. Then, a learner's profile is created and the process of information collecting begins, i.e. learner's ID, learning styles, prior knowledge, and particular learner's activities in the system, etc. All the information is stored in the database and used for the proposed method, data processing, and recommendation of a personalized learning path.

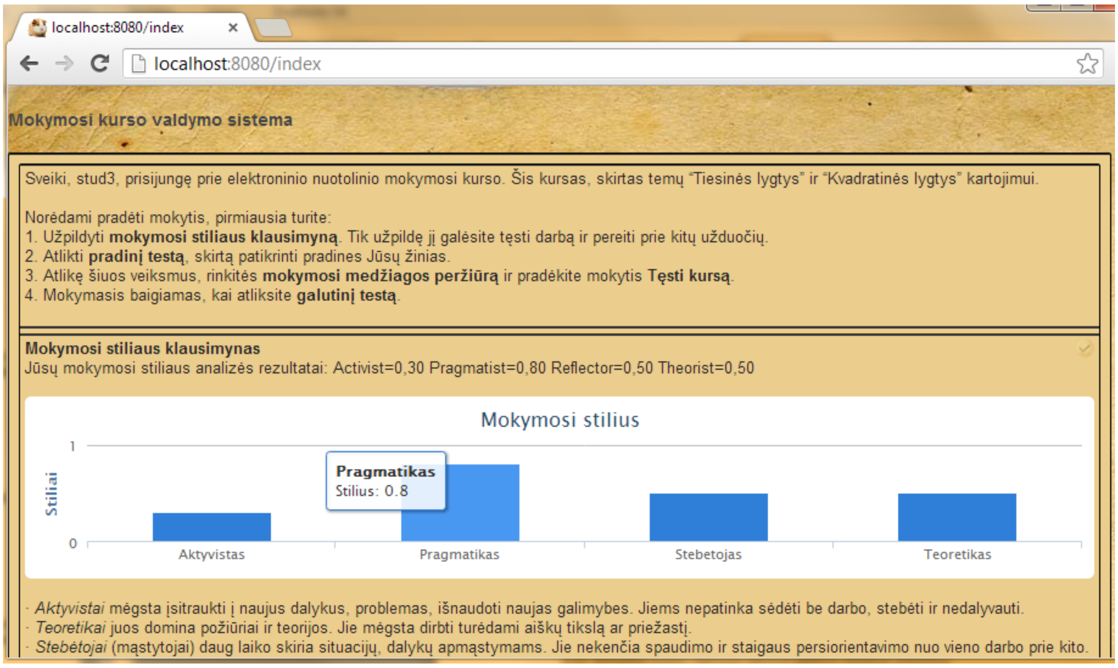

Fig. 4.3. A window of the prototype of the system

4.1.4 Data collection

At this stage, the following information required to implement the method was collected as follows:

1. *Learning styles questionnaire*. The questionnaire consists of 40 questions. One answer – 1 point.
2. *Pre-test* and *post-test*. The maximum number of points in both tests – 12, the minimum – 0. The correct answer – 1 point.
3. *Log files*. The transactional log data of all learners' interactions with the system. Logs were recorded over a certain period of time. The data of record files come from several sources as follows:
   a) A learner's click on any element of the system interface is recorded; this record contains the duration of the action, the interface element ID, and the learner's ID.
   b) A learner's reactions to the recommendation; there were two ways to react to it: he/she can ignore it by selecting any desired LO or can follow the recommendation. The two types of learners' reactions are being recorded; these records contain the time of reaction, the recommended resource ID, the learner's ID, the type of reaction, and other data.

These records were used to analyze learning paths of learners and their response to recommendations (in the case the learner is in one of the "recommendation" group).

The next two sections describe the data collection procedure, and formally state the research hypotheses in the experiment.

4.1.5 Data analysis

619 participants (mainly eighth-grade learners) took part in the experiment.

Participating schools and learners were selected in the way that Mathematics learning outcomes averages are similar. Participants of the experiment were divided into control group (88 learners) and the experimental group (531 learners). Lessons were planned in a way to allow students to learn (or repeat) topics “Linear Equations” and “Incomplete quadratic equation”. The initial and final tests were carried out in the classroom. Learning using the system in between the initial and final test took place in a remote location. The experiment lasted for 3 months from 2013 March to 2013 June. Each group was trained how to use the system in the beginning of the experiment.

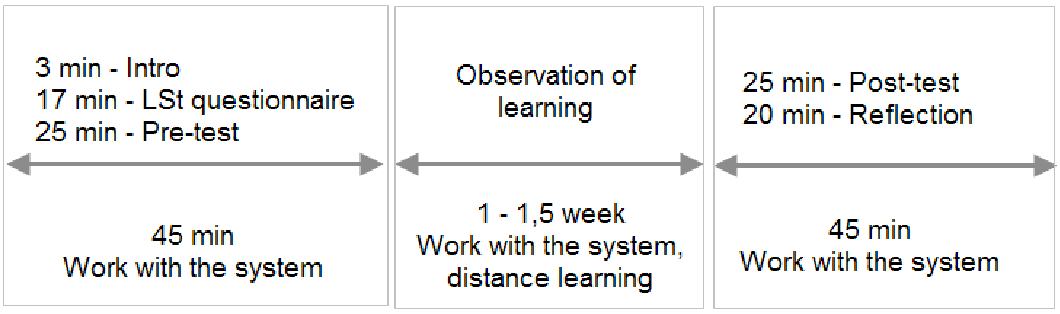

Fig. 4.4. A strategy of the experiment

The experiment was executed by strategy described by in Figure 4.4. The strategy consisted of three phases:

1. Learners that were trained to use system had carried out the learning style questionnaire and the initial test (done in classrooms for 45 min.).
2. Phase lasted from 1 to 1.5 weeks. Learners were studying materials using the system. In most of times remote access from home was used.
3. Phase was organized in classes (duration 45 minutes). In this lesson, learners made the final test and spent the rest of time for reflection on learning and performance.

The key aim of this experiment was to investigate whether the proposed method for personalization of a learning unit by recommending LOs for learners improves their learning results and saves the learning time. Three questions were raised as follows:

1. What impact has usage of the system with recommendations on learners’ learning results?
2. What impact has usage of the system with recommendations on learners’ learning time?
3. What impact has usage of the system with recommendations on learners’ learning results according to their learning styles?

To answer these questions, a quazi-experiment was carried out, and the results obtained were analysed using the *t-test* statistical technique of two independent samples. For statistical analysis, the SPSS package for Windows OS was used.

To evaluate whether the proposed LOs recommendations have a positive impact on the effectiveness of learners’ learning compared to no-recommendation learning, two metrics were used (the first and the second questions):

a) The average of the positive change in the grade.
b) The average time spent for learning.

The following hypotheses have been evaluated based on these metrics:

1) H_1: The system with recommendations increases *the average of the positive change in the grade* compared to the system having no recommendations.

2) H_0: There is no influence on *the average of the positive change in the grade* compared to the system having no recommendations.
3) H_1: The system with recommendations decreases *the average of time spent for learning* compared to the system having no recommendations.
4) H_0: There is no influence on *the average of time spent for learning* compared to the system having no recommendations.

To answer the third question about the impact of usage of the system with recommendations on learners' learning results according to their learning, a descriptive statistical analysis has been used.

4.2 Results of the experiment

To test the research hypotheses of the quasi-experiment done, the *t-test* statistical technique of two independent samples was used. The difference of statistical significance was observed among averages on the level of significance ≤ 0.05 (denoted *Sig. 2 - tailed*).

Three groups were compared: 1) the first group of learners who used less than 30% of recommendations; 2) the first group of learners who used from 30% to 70% of recommendations, and 3) the third group of learners who used more than 70% of recommendations. Note that those learners who used more recommendations have achieved higher learning results. The statistical analysis of the data shows that, although there is a positive impact of usage of the system with recommendations on learners' learning results, however, a statistically significant difference was obtained only between two groups, i.e. those who used less than 30% of recommendations, and those who used more than 70% of recommendations ((Fig. 4.5. a) marked by a red rectangle), $p = 0.002 \leq 0.05$.

Comparing the average of time spent for learning among all the groups, we have observed that those learners who did not use the recommendations spent more time than that those who did. However, the learners who used more than 70% of recommendations spent more time for learning than that those who followed from 30% to 70% of recommendations. A statistically significant difference was obtained only between two groups: those who used less than 30% of recommendations, and those who used more than 70% of recommendations ((Fig. 4.5. b). marked by a red rectangle), $p = 0.002 \leq 0.05$.

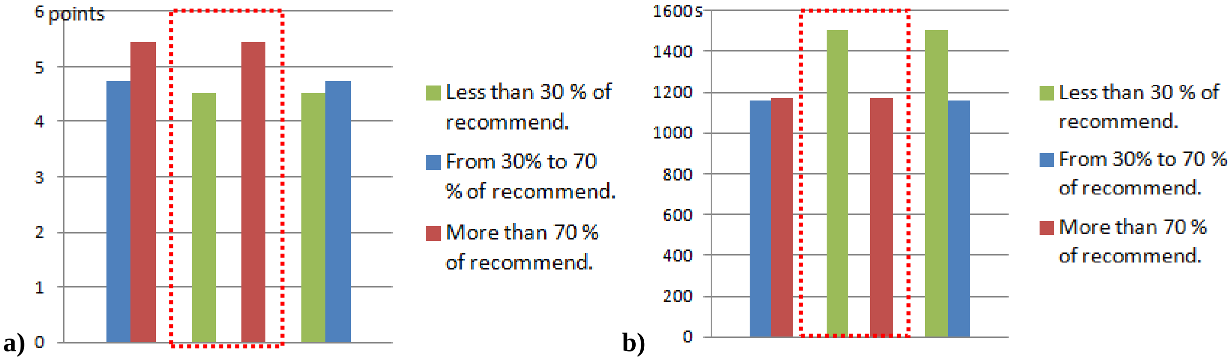

Fig. 4.5. Comparison of the average a) of learning results and b) of time spent for learning

In order to evaluate the efficiency of recommendations, along with the proposed a multiple criteria set approach, the relationship between learning styles and learning results was investigated. It is concluded that the method affects the learning results – system is not effective in case where the learner has all the learning styles expressed or zero learning styles (Figure 4.6).

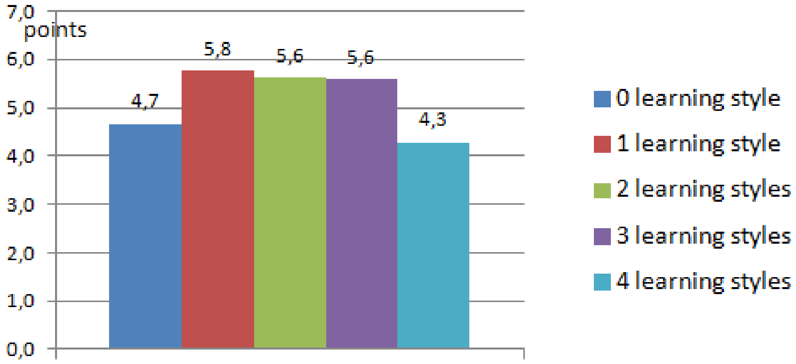

Fig. 4.6. Comparison of the average of learners' learning results according to their learning styles

GENERAL CONCLUSIONS AND RESULTS

1. The adaptive method for personalization of learning units has been created. The method allows finding optimal learning paths according to learners' learning styles. The method is working both in static and dynamic learning units.
2. In order to adapt Ant Colony Optimization to the e-learning that could find optimal learning paths for learners according to their learning styles and working both in static and dynamic learning units, Ant Colony Optimization has been modified. Although the parameters and functions used in this work are the same as defined in original Ant Colony Optimization, there are two novel extensions for e-learning as follows:
   a) The multiple criteria model of learning styles has been proposed. A learner is modelled as a multiple criteria set B = LSt({w1, w2, w3, w4}), where {w1, w2, w3, w4} are the values of learner's learning style.
   b) In contrary to other researchers' work, personalization of a learning unit is considered in this work as a dynamic research object. Therefore, with a view to achieve a more efficient application of the method in dynamic learning environment, a novel method modification based on "new component" pheromone integration was proposed.
3. The computer simulations have shown that the method proposed is suitable to solve the problem formulated while finding learning paths according to learners' learning styles. The proposed pheromone updating strategy is unique, and the valuable results obtained complement the previous research results in this area.
4. The results of a pilot study have shown that there is a statistically significant difference among learners' with different learning styles learning activities in the system by applying the adapted styles identification questionnaire. The obtained results have proved that there is a need for modelling learning styles as a multiple criteria set. It is also proved that although learning is affected by multiple factors the learning style is one of the most important.
5. The results of the empirical experiment performed have shown that the method's application for learning in e-system allows finding learning paths according to learners' learning styles and this improves learning results and saves their learning time.

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SHORT DESCRIPTION ABOUT THE AUTHOR

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In 2000, she graduated from Vilnius Secondary School No. 45 cum laude. In 2004, she acquired a Bachelor's Degree in Mathematics from Vilnius University, Faculty of Mathematics and Informatics. She gained a Master's Degree in Mathematics at Vilnius University, Faculty of Mathematics and Informatics in 2006.

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SANTRAUKA

Darbo aktualumas

Pagrindinis informacinių technologijų naudojimo mokymuisi tikslas – didinti mokymosi kokybę ir efektyvumą, tobulinti besimokančiojo ir mokytojo darbą. Šiuolaikinis mokymasis neįsivaizduojamas be informacinių technologijų ir jų teikiamų galimybių panaudojimo. Vienas iš tokių galimybių pavyzdžių – mokomieji objektai ir mokomieji moduliai. Tačiau be šių el. mokymosi komponentų personalizavimo, individualių mokymosi kelių parinkimo yra galimas tik dalinis kokybinis efektas.

Pagrindinis personalizuoto mokymosi principas teigia, kad nėra unikalios vienintelės mokymo strategijos tinkančios visiems besimokantiesiems, todėl didžiąja dalimi sėkmingas mokymosi tikslų pasiekimas priklauso nuo to, kaip mokymo ir mokymosi procese atsižvelgiama į individualius besimokančiųjų skirtumus. Daugelis autorių akcentuoja, kad mokymosi proceso personalizavimas gerina besimokančiųjų mokymosi efektyvumą, produktyvumą. Personalizavimas gali būti įgyvendinamas iš dviejų perspektyvų: mokytojo ir besimokančiojo. Žvelgiant iš mokytojo perspektyvos personalizuotas mokymasis įgyvendinamas remiantis mokytojų patirtimi, intuicija, tačiau besimokančiųjų atžvilgiu tai ne visada bus efektyvu. Personalizuotas el. mokymasis įgalinamas kuriant ir projektuojant adaptyvias, intelektualias sistemas. Vis dažniau šiuolaikinės mokymo sistemos projektuojamos remiantis metodologija „Apačia-viršus“, siekiama, kad sistema, analizuodama ir remdamasi istoriniais naudotojų duomenimis, priimtų sprendimus, modeliuotų mokymosi procesą iš besimokančiųjų perspektyvos, t. y. gebėtų adaptuotis sparčiai kintančioje aplinkoje, mokymo procesą taikyti prie besimokančiųjų, mokomąją medžiagą pateikti ne tik dalykiškai tikslią, kokybišką, bet ir individualiai atsižvelgti į besimokančiojo žinių lygį ir kitus poreikius. Darbe tiriama mokomųjų modulių personalizavimo problema ypatingą dėmesį skiriant mokymosi kelių išskyrimui pagal besimokančiųjų mokymosi stilius.

Personalizavimas mokomojo turinio atžvilgiu nagrinėjamas dvejopai: kai besimokančiajam parenkamas tik vienas mokomasis objektas arba kai parenkama visa mokomųjų objektų aibė, t.y. mokomasis modulis. Nors mokslinėje literatūroje pirmasis atvejis įvardijamas kaip mokomojo objekto parinkimo problema, o antrasis kaip mokymosi sekos parinkimo problema, tačiau sprendžiant abi problemas keliamas vienas esminis klausimas – kaip efektyviai, kokybiškai parinkti mokomuosius objektus besimokantiesiems pagal jų poreikius. Vienas būdų minėtai problemai spręsti yra kolektyvinės intelektikos metodų taikymas. Literatūroje randama tyrimų susijusių su mokomojo modulio personalizavimu, kai personalizavimas apibrėžiamas kaip tinkamo besimokančiajam mokymosi kelio parinkimas. Remiantis atlikta analize, pastebėta, kad buvo tirti tik statiniai mokomųjų modulių atvejai, tačiau realiame gyvenime, mokomieji moduliai keičiami, pvz., pridedant, šalinat, apjungiant mokomuosius objektus. Be to, pasigendama išsamesnių tyrimų ir įvertinimų, rekomendacijų ir konkrečių realizavimo pavyzdžių.

Darbe tiriamos kolektyvinės intelektikos, skruzdžių kolonijos optimizavimo metodo, galimybės taikyti jį el. mokymuisi, siekiant sukurti adaptyvų mokomųjų modulių personalizavimo metodą gebantį suformuoti optimalius mokymosi kelius besimokantiesiems pagal jų mokymosi stilius ir veikiantį tiek statiniuose, tiek dinaminiuose mokomuosiuose moduliuose.

Darbo objektas

Darbo tyrimo objektas yra mokomieji moduliai ir jų personalizavimas.

Darbo tikslas ir uždaviniai

Pasiūlyti adaptyvų mokomųjų modulių personalizavimo metodą, parenkantį mokymosi kelius pagal besimokančiųjų mokymosi stilius, siekiant gerinti besimokančiųjų mokymosi rezultatus ir trumpinti mokymosi laiką.

Darbo tikslui pasiekti formuluojami šie uždaviniai:

1. Ištirti el. mokymosi komponentus (mokomuosius objektus, veiklas, aplinkas, modulius) bei personalizuoto el. mokymosi technologinius ypatumus (adaptyvių sistemų funkcijas, jose naudojamų komponentų savybes).
2. Išanalizuoti esamus personalizuoto mokomojo modulio tinkamumo besimokantiesiems nustatymo metodus.
3. Sukurti adaptyvų mokomųjų modulių personalizavimo metodą, parenkantį mokymosi kelius atsižvelgiant į besimokančiųjų mokymosi stilius, taikant skruzdžių kolonijos optimizavimo algoritmą statinio ir dinaminio mokomojo modulio atvejams.
4. Atlikti sukurto metodo taikymo eksperimentinį aprobavimą.

Tyrimo metodika

Rengiant analitinę disertacijos dalį buvo atlikta mokslinės literatūros analizė. Šios analizės rezultatai: ištirti mokomojo modulio komponentai, išanalizuoti personalizuoto el. mokymosi technologiniai ypatumai bei atlikta personalizuoto mokomojo kelio tinkamumo nustatymo besimokančiajam metodų apžvalga. Ja remiantis, siekiant darbe iškelto tikslo, buvo pasirinktas vienos iš dirbtinio intelekto metodų grupių – kolektyvinės intelektikos taikymas.

Kuriant adaptyvų mokomųjų modulių personalizavimo metodą, buvo taikomi matematinio modeliavimo ir kompiuterinių simuliacijų metodai. Buvo atlikti du virtualūs eksperimentai. Pirmuoju eksperimentu buvo tiriamas metodo tinkamumas mokomajam moduliui personalizuoti pagal mokymosi stilius. Tyrimas parodė, kad metodas tinkamas jį taikyti parenkant mokymosi kelius. Antrasis eksperimentas buvo skirtas ištirti metodo veikimo efektyvumą dinaminių mokymosi modulių atveju. Nagrinėtas tik vienas atvejis, kai pridedami nauji mokomieji objektai. Jo metu buvo nustatytos efektyvesnio metodo veikimo sąlygos. Kompiuterinių simuliacijų metu gauti duomenys buvo analizuojami aprašomosios statistikos metodais.

Siekiant patikrinti sukurto metodo praktinį taikymą ir suformuluotas hipotezes buvo sukurtas virtualiosios mokymosi aplinkos prototipas, realizuojantis sukurtą metodą. Atliktas kvazieksperimentas, kurio metu buvo dirbama su realiais prototipe sukauptais duomenimis, stebimi 8 klasių mokiniai ir jų veiksmai sistemoje. Analizuojant duomenis taikytas dažnių skaičiavimas ir dviejų nepriklausomų imčių *t-test* statistinės analizės metodas.

Mokslinis naujumas

1. Sukurtas adaptyvus mokomųjų modulių personalizavimo metodas parenkantis optimalius mokymosi kelius besimokantiesiems pagal jų mokymosi stilius ir veikiantis tiek statiniuose, tiek dinaminiuose mokomuosiuose moduliuose.
2. Siekiant pritaikyti skruzdžių kolonijos optimizavimo metodą el. mokymui(-si), parenkantį optimalius mokymosi kelius besimokantiesiems pagal jų mokymosi stilius ir veikiantį tiek statiniuose, tiek dinaminiuose mokomuosiuose moduliuose, skruzdžių kolonijos optimizavimo metodas buvo modifikuotas. Nors parametrai ir funkcijos yra tokios pačios kaip ir originaliame skruzdžių kolonijos optimizavimo metode, darbe siūlomi du originalūs sprendimai:
   a) Besimokančiojo profilis aprašomas daugiakriteriniu modeliu B = (MSt({w1, w2, w3, w4})), kur {w1, w2, w3, w4} yra mokymosi stilių reikšmės.
   b) Mokomasis modulis priešingai nei kituose moksliniuose tyrimuose, nagrinėjamas kaip dinaminis tyrimo objektas, todėl siekiant efektyvesnio metodo veikimo dinaminėje mokymosi aplinkoje, pasiūlyta nauja metodo modifikacija, grįsta „naujo komponento“ feromono integracija į esamą metodą.

Praktinė darbo reikšmė

Atlikto empirinio eksperimento rezultatai rodo, kad metodo taikymas mokinių mokyme(-si) el. sistemoje leidžia surasti mokymosi kelius mokomajame modulyje atsižvelgiant į jų mokymosi stilius ir gerina jų mokymosi rezultatus, taip pat trumpina mokymosi laiką.

Pasiūlytas metodas gali būti naudingas kursų kūrėjams, siekiant lengviau prižiūrėti, atnaujinti ir tobulinti mokomuosius modulius ir kursus.

Ginamieji teiginiai

1. Skruzdžių kolonijos optimizavimo algoritmas yra taikytinas statinių ir dinaminių mokomųjų modulių personalizavimui suformuojant personalizuotus mokymosi kelius grįstus besimokančiųjų mokymosi stiliais.
2. Sukurtas adaptyvus mokomojo modulio personalizavimo metodas gerina besimokančiųjų mokymosi rezultatus ir trumpina mokymosi laiką.

Darbo struktūra

Darbą sudaro: terminų ir santrumpų žodynėlis, keturios pagrindinės dalys – skyriai, išvados ir rezultatai, naudotos literatūros sąrašas ir priedai. Darbo apimtis yra 138 puslapiai. Tekste panaudoti 39 paveikslai, 6 lentelės ir 7 priedai. Rašant disertaciją buvo naudotasi 163 literatūros šaltiniais.

Pirmajame skyriuje pateikiamas darbo įvadas. Pristatomas darbo aktualumas, darbo tikslai ir uždaviniai, tyrimų metodai, mokslinis naujumas, praktinė darbo reikšmė, ginamieji teiginiai ir darbo aprobavimas.

Antrajame skyriuje nagrinėjamos teorinės darbo prielaidos, kuriomis buvo remiamasi kuriant ir aprašant adaptyvų mokomojo modulio personalizavimo metodą. Nagrinėjami el. mokymosi komponentai, adaptyvaus personalizuoto el. mokymosi aspektai, esami personalizuoto mokomojo modulio tinkamumo besimokančiajam nustatymo metodai.

Trečiajame skyriuje aprašomas sukurtas adaptyvus mokomųjų modulių personalizavimo metodas, gebantis suformuoti optimalius mokymosi kelius besimokantiesiems pagal jų mokymosi stilius ir veikiantis tiek statiniuose, tiek dinaminiuose mokomuosiuose moduliuose. Skyriuje aprašomos metodo kūrimo prielaidos, mokomojo modulio struktūra, besimokančiojo profilio sudarymo schema, matematiniu modeliu pateikiama mokomojo modulio personalizavimo problema, aprašomas sukurtas metodas. Taip pat pateikiami atlikti kompiuteriniai eksperimentai ir pristatomi gauti rezultatai.

Ketvirtajame skyriuje, remiantis empirinio eksperimento rezultatais, pateikiamas sukurto metodo vertinimas. Aprašomas įvykdytas eksperimentas, sukurtas el. sistemos prototipas, atskleidžiami metodo taikymo ypatumai.

Darbo pabaigoje pateikiamas rezultatų apibendrinimas ir išvados.

Prieduose pateikiama: mokymosi stilių klausimynas, sukurtos mokymosi aplinkos prototipo langai, atliktų tyrimų aprašai ir rezultatai.

Bendrosios išvados ir rezultatai

1. Sukurtas adaptyvus mokomųjų modulių personalizavimo metodas optimaliems mokymosi keliams pagal besimokančiųjų mokymosi stilius parinkti. Metodas tinka statiniams ir dinaminiams mokomiesiems moduliams.
2. Skruzdžių kolonijos optimizavimo metodas el. mokymui(-si) modifikuotas taip, kad galėtų būti taikomas optimaliems mokymosi keliams pagal besimokančiųjų mokymosi stilius parinkti ir tiktų tiek statiniams, tiek dinaminiams mokomiesiems moduliams. Nors parametrai ir funkcijos yra tokios pačios kaip ir originaliame

skruzdžių kolonijos optimizavimo metode, darbe siūlomi du originalūs sprendimai jo taikymo el. mokyme(-si):

a) Besimokančiojo profilis aprašomas daugiakriteriniu modeliu B = (MSt({w1, w2, w3, w4})), čia {w1, w2, w3, w4} mokymosi stilių reikšmės.

b) Mokomasis modulis, priešingai nei kituose moksliniuose tyrimuose, nagrinėjamas kaip dinaminis tyrimo objektas, todėl siekiant efektyvesnio metodo veikimo dinaminėje mokymosi aplinkoje, pasiūlyta nauja metodo modifikacija, grįsta „naujo elemento“ feromono integracija į esamą metodą.

3. Atliktų kompiuterinių eksperimentų rezultatai patvirtino, kad pasiūlytas metodas tinka iškeltai problemai spręsti, parenkant mokymosi kelius besimokantiesiems pagal jų mokymosi stilius. Pasiūlyta feromonų atnaujinimo strategija yra unikali, gauti naudingi rezultatai papildo ankstesnius šios srities tyrimų rezultatus.
4. Žvalgomojo tyrimo rezultatai parodė, kad egzistuoja statistiškai reikšmingas skirtumas tarp skirtingų mokymosi stilių grupių veiklų el. sistemoje, taikant adaptuotą mokymosi stilių nustatymo klausimyną. Remiantis tyrimo rezultatais, patvirtinamas mokymosi stilių aprašymo daugiakriteriniu būdu tikslingumas ir parodoma, kad, nors mokymuisi daro įtaką daug faktorių, mokymosi stiliai yra vienas svarbiausių.
5. Atlikto empirinio eksperimento rezultatai rodo, kad metodo taikymas besimokančiųjų mokymui(-si) el. sistemoje leidžia parinkti personalizuotus mokymosi kelius atsižvelgiant į jų mokymosi stilius, gerina besimokančiųjų mokymosi rezultatus, taip pat trumpina mokymosi laiką.

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