Genetic Algorithm Based Adaptive Learning Scheme Generation For Context Aware E-Learning

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***Abstract*—Context aware e-learning system helps to provide e-learning contents which are customized according to the learner's context. For generating context aware contents many adaptation parameters have to be considered. Customized learning path is one such adaptation parameter. In the existing e-learning systems, learning paths is generated using several approaches. But in order to generate context aware contents, the profile context, infrastructure context, preference and learning context of learner have to be considered in addition the learning path. These context parameter values together constitute for the learning scheme of a learner. Hence learning path generation has to evolve into a learning scheme generation which accommodates the entire learner's context. There are no learning scheme generation algorithms reported in the literature. In this paper a genetic algorithm based adaptive learning scheme for context aware e-learning has been described.**

Keywords- E-learning, Context Aware E-learning, Adaptive Learning Path generation, Genetic Algorithm

I. INTRODUCTION

Internet has become accessible for wide parties of contemporary societies and its role continuously widens [8]. One of the interesting usages of Internet is e-learning. E-learning system has become widely used in educational society because of its advantages on enabling learning anywhere and anytime. In e-learning, delivery of learning contents should adapt to the pre-knowledge of the learner, learner's pace of learning, level of comprehension etc. The early e-learning platforms do not include these characteristics and ends up with static inflexible e-learning system.

Context aware e-learning system provides the learning contents based on the individual characteristics of the learner, where context is referred as any information that can be used to characterize the situation of an entity where an entity can be a person, place and a physical or computational object.

There are many learner's parameters considered for context aware e-learning system. These parameters are used for generating learning path. Learning path defines the sequence of learning activities that is carried out by the learner going through learning units in e-learning system. Learning unit is an abstract representation of a course, a lesson, a workshop, or any other formal or in-formal learning or teaching event [6].

Selection of appropriate learning contents and delivery of them to learners are challenging tasks of e-learning, because the learning content must be provided to an acceptable level of the learner's understanding. In the literature, there are many approaches for generating learning paths. But the drawback of existing approaches are, they are not fulfilling all the learner's context such as profile context, infrastructure context, preference and learning context. So a learning scheme has to be devised, which includes all the contexts of a learner. This helps the learner to get most suitable study material. Since there are only learning path generation algorithms available in the literature, there is a necessity to devise algorithms for generating learning schemes. A genetic algorithm-based adaptive learning scheme generation algorithm is described in this paper.

The whole paper is organized as follows: Section II provides an overview of the existing techniques of adaptive learning path generation techniques after categorizing each of these techniques under appropriate nomenclature. Proposed Genetic algorithm based adaptive learning scheme generation algorithm is given in Section III. The need for proposed algorithm is described in Section IV. In Section V the implemented system is described. Section VI concludes the paper.

II. EXISTING APPROACHES OF ADAPTIVE LEARNING PATH GENERATION

There are different approaches found in the literature for adaptive learning path generation. Here, these approaches are categorized based on the techniques used for learning path generation. The following section describes each approach briefly.

A. Domain Modelling

It is very important to provide rich representation of the existing learning objects in order to enable their effective retrieval. So representation of domain knowledge which is known as domain modeling [1, 4, 10, 13, 16, 17, 18, 20, 27] is a key starting point to implement flexible and adaptive mechanism in e-learning. There are different techniques used for this. The following section describes each technique.

1) Learning Path Graph

Here a Learning Path Graph describes the structure of domain knowledge in-hand and the associated learning goals. Designing the domain model consists of two processes, the process of designing a hierarchy of learning goals as well as concept.

The learning path graph [17] (LPG) is a directed acyclic graph which represents all possible learning paths that matches the learning goal in hand.

To construct the LPG, for each concept of the Concept Path graph, related learning resources are selected from media space. Media space describes the educational characteristics of the learning resources.

A personalized learning path is selected from the graph that contains all the available learning paths, based on learner's attributes in the user model. User model consist of learner knowledge space (level of expertise) and cognitive characteristics (learning style) and preferences. Suitability function is used for weighting each connection of the Learning path graph for providing suitability factor for learning resources. From the weighted graph, the most appropriate learning path is selected for a specific learner by using shortest path algorithm.

2) Concept Map

The domain knowledge is represented by Concept Maps [4, 13, 20]. Using this graphical representation of ontology, the whole courseware structure and core knowledge about a subject domain can be clearly revealed. Graphical ontology based concept map is constructed based on the clustered courseware and the concept correlation matrix. For grouping courseware with high correlation into the same clusters, fuzzy clustering analysis schemes are used. Concept correlations within the same cluster are expected as high as possible. Concept map provide much more meaningful information to describe courseware structure. It makes learner to realize the relation of pre/post learning concepts among courseware, and also supplies learners with effective scaffolds and guidance for learning. Due to the clustering algorithm, some courseware with high concept relation can be grouped together. It thus makes learners learn in systematic way and provides them with better and complete courseware structure information.

3) Ontology

Domain ontology is used to describe learning materials that compose together to form a course. It is capable of providing adaptive e-learning environments and reusable educational resources. The ontology is represented by a set of abstract concepts /topics and semantic link between them instead of the actual learning material [10, 13, 27]. The concept that constitutes the knowledge of the treated domain is collected in class Concept. This class contains data type property conceptName to identify the concept, and other object properties that allow establishing different relations among domain concepts. The e-learning system compares the user's learning style with the resources learning style possibilities. This way, the learning materials that best fit the student's individual request are dispatched.

4) Learning Activity Graph Curriculum Sequence

A Learning activity may be any object from a simple exercise to a complex course. Learning activity graph [27] is used to organize learning resources in a learning task. The learning activities are organized as a directed graph with pre-condition and post-conditions in each node.

The nodes of the graph can be either simple learning activity or sub-learning activity graph involving several related learning resources for a sub-learning task. Learning activity sequencing algorithm integrates the use of learner model and learning activity graph for learning activity sequencing based on learner preference and level of expertise. This approach can generate efficient corresponding learning activity sequences for various learners, and record learner's learning processes and achievements to update the user model.

B. Constraint Satisfaction Handling

Learning unit's sequences are defined in terms of competencies in such a way that sequencing problem can be modelled like a classical Constraint Satisfaction Problem (CSP) [12]. In this, constraints are defined for learning resources such as pre-requisite and post requisite of a course. For constructing adaptive learning path, or solving Constraint Satisfaction problem, genetic programming and swarm intelligence techniques are used.

1) Genetic Programming

For constructing learning path in this approach, different types of curricula are taken [5, 14]. A serial number is assigned to each curriculum. The initial population size is fixed as 50. A fitness function is generated to judge the quality of the generated learning path. For determining the fitness function, results of pre-test taken by the user, difficulty parameters of the curriculum and the concept relation degrees of the curriculum are considered. Reproduction operation, mutation operation and cross over operations are carried out to find the next generation of learning paths. Each generation of learning paths is evaluated using fitness function and best satisfied learning path is selected.

2) Swarm Intelligence

It is a type of artificial intelligence technique which is based on the collective behaviour of decentralized, self organizing systems. Particle Swarm Optimization (PSO) is an evolutionary computing optimization algorithm. PSO mimics the behaviour of social insects like bees. Random initialized particles population flies through the solution space sharing the information they gather. Particles use this information to dynamically adjust their velocity and cooperate towards finding a solution.

The domain knowledge is classified as different learning objects such as basic courses, itinerary courses, compulsory courses and elective courses [12].

Competency records are created to specify learning object restrictions, and learning object metadata records are updated to reflect pre-requisite and learning outcome competencies. Once the problem is established, PSO agent parameters are set to find out best feasible learning path.

C. Clustering of Users

In this approach [8], instead of generating single path for every individual learner, the learners are grouped into clusters of different learning styles and a learning path corresponding to the cluster into which he is classified is generated.

1) Neural Networks

In this technique, an intelligent agent called Learning Assistant is used [8]. Functionalities of Learning Assistant are two fold. 1) Training the Neural network by classifying every pupil into different clusters of learners based on their level of expertise, learner preferences and learning pace. 2) Generating the learning path that is appropriate for the cluster into which the pupil has been classified.

Self Organizing Map (SOM) neural network is used for grouping similar pupils. SOM operates in two modes: training and mapping. Training builds the map using input examples. It is a competitive process also called vector quantization. Mapping automatically classifies new input vector, i.e., it classifies a new pupil into one of the learner clusters. Learning Path for this pupil is generated based on the learning path that is appropriate for the cluster to which the pupil has been classified by the trained SOM.

D. Case Based Reasoning

Case based reasoning [14] (CBR) means adapting old solution to meet new demands, using old cases to explain new situation, or reasoning from precedents to interpret a new situation. The planner of CBR must be a learning system because it must reuse its own experience. CBR requires a knowledge based learning that makes the planner understand what should be learned and when it should be learned. A new case means that the learner fail to reach the mastery level in current unit. Therefore, a new learner case will trigger the CBR system to predict the probabilities of that specific case. The reasoning of the CBR mechanism will start to search for the case most similar to the new case in order to support the corrective activity.

E. Learning Profile of Previous Users

This approach [9, 23, 26] generates adaptive learning path by taking the previous user's learning profile by using an extended ant colony system approach. Ant Colony techniques that are employed for providing adaptivity are discussed in the following section.

1) Ant colony

Ant Colony Optimization is used to predict the best path for the student taking into account the users profile and the paths followed by the earlier students of the e-learning content.

Attribute–based Ant Colony System (AACS) [26] is an extension of Ant Colony system. It is a method of finding learning objects that would be suitable for a learner based on the most frequent learning trails followed by the previous learners. The system updates the trails pheromones from different knowledge levels and different styles of learners to create a powerful and dynamic learning object search mechanism. There are three prerequisites for achieving this a) the adaptive learning portal knows the learner's attributes which include the learner's knowledge level and learning style b) the learner's attributes and learning object's attributes which have been annotated by teacher or content providers c) Matching the relationships between learners and learning object.

F. Statistical Approach

In this approach, statistical methods such as Bayesian probability theory are used for finding the adaptive learning path [9, 15]. This is described in the following section.

1) Bayesian Networks

Bayesian network [9, 15] is a directed graph whose nodes represent the uncertain variables of interest and whose edges are the casual or influential links between the variables. Associated with each node, a node probability table will be there, which contains conditional probability values.
Learning path generation using Bayesian Networks includes two steps. The first step creates a node probability table based on Bayesian Probability Theory. The probability table

indicates the probability of the various subsequent nodes which could be traversed from the current node. This probability value is assigned based on level of expertise, learning style and learning pace of a learner and are called candidate learning paths. The second step is to construct Bayesian network, to calculate probability value which represents for each knowledge unit in learning path. From this, the shortest path is selected to provide the appropriate learning path for a learner.

G. Automatic Generation of Learning Path Algorithm

This approach promotes active learning by allowing construction of courses which are personalized in terms of both contents and teaching materials [24]. Personalization is based on each student's profile in which level of expertise, learner preference and learner intentions are mentioned. Thus, it provides students with an adaptive environment which dynamically adjusts the course contents during the learning process. The algorithm allows a student to attend on-line courses. Each student logs into the system by specifying his membership in a given user class. Then he chooses a course and consequently all the related learning paths are built, based on student's needs. Finally, the student selects one of these paths and attends the course, which also includes exercises and tests.

H. Weighted Learning Object

This approach [2] includes three main phases to generate adaptive course contents. The first phase is evaluating learning process of the student. The second phase is selecting course contents suitable for each learner corresponding to the learner model based on the weights of the learning object. Each course's material such as text, images, video is stored in learning object database and supplement some attributes for each learning object such as difficulty level of learning object, total time needed for studying etc. And assign a value in between 0 and 1 to each attribute. This is taken as weight of the learning object. Adaptive course content generation is based on learner's level of expertise, learning preferences and learner intentions. The last phase is selecting view model of the course for each learner.

I. Petri Nets Based Approach

A Petri net consists of two kinds of nodes called places and transitions where arcs connect them. To describe the behaviour of a system, time can be associated with attributes like places (called P-timed), tokens (called age) and transitions (called T-timed) [19, 25]. In a P-timed Petri nets, if attribute is associated with place, the firing rules take a fixed, finite amount of time delay, the transition becomes enabled.

Students learning activities in web based environment are series of discrete events, such as reading hypertext, typing words and clicking hyperlinks. These activities helps students move in hyperspace. The first step for adaptation is to build a P-timed Petri Net based model for hypertext learning state space. Then the learning state is mapped onto places and when a place receives tokens, its knowledge node become accessible to students. Students are required to concentrate on current learning state and freely select knowledge node inside the current state.

The context parameters used for each approach are tabularized in the table 1. From the table it is clear that all the learning path generation approaches are considering very less number of context parameters, which is not enough to capture the entire contexts of learner. So instead of learning path generation, adaptive learning scheme generation algorithm which generates customized learning content by considering all the context parameters has to be devised which is explained below.

III STRUCTURE OF NEWLY PROPOSED ALGORITHM

For generating a learning scheme, three levels of contexts of learner are to be considered. They are Content level, Presentation level and Media level contexts. Fig 1. illustrates the context structure needed to be considered for generating context-aware learning contents.

Content layer deals with learning path generation. The individual learning path generation is important because different learners may have different characteristics, prior knowledge or motivation or needs.

The second level, Presentation level mainly concentrates on the learner's preferences and intentions. For example, a learner may prefer to learn a content material by Concept, Detailed Concept, Example, Case study, Simulation and Demonstration etc. Here, concept, detailed concept, example, etc represent the different abstractions in which a particular learning object may be present. The intention of a learner coming to an e-learning system may be related to research, survey work, interview purpose, assignment work, project work etc. or just to obtain a general introduction of the subject of study. Based on the intentions, the different abstractions of a learning object chosen for presentation to the learner will change. For example, if a learner comes with interview intention, the abstractions of a learning object chosen for presentation would be Concept, Example and Case study. If the learner's intention of study is for submitting an assignment, then the abstractions of a learning object chosen for presentation would be Detailed Concept, Example and Case Study. Likewise, for other intentions, the various abstractions of a learning object chosen for presentation vary. Table 2 shows abstractions of learning objects chosen for various learning intentions.

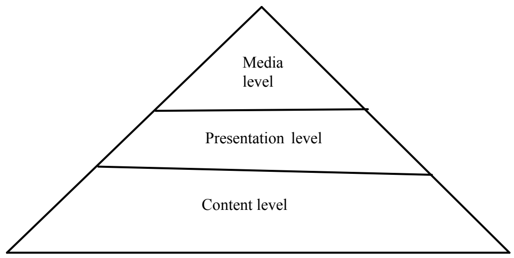

Figure1. Structure of learning Context

TABLE 2. Abstraction of Learning Object chosen for various learning Intentions

Intention	Abstractions of learning object
Research	Concept, Detailed Concept, Example, Case Study, Demonstration, Simulation
Survey	Detailed Concept, Example, Case Study
Interview	Concept, Example, Case Study
Seminar	Detailed Concept, Case Study, Demonstration, Example
Project	Detailed Concept, Case Study, Example, Simulation, Demonstration
Assignment	Detailed Concept, Example, Case Study
Basic Introduction	Concept, Example

The various abstractions of a learning object which are chosen for presentation based on the preference and intention have to be sequenced based on the psychology of the learner. For example, if the psychology of a person is extrovert and he prefers to learn by demo and he has come with research intention, the abstractions of the learning object chosen and their sequencing are as given below.

Concept, Demonstration, Case Study, Simulation, Example, Detailed Concept

The sequence for extrovert lays emphasis on practical learning rather than by concept. That is why, the demo, case study and simulations abstractions are sequenced before the detailed concept abstraction. Table 3 shows the sequencing of the chosen abstractions of learning object based on psychology for a person coming with research intention.

The third level, considers the media preference of a learner. Media can be audio, video, text or animation. Accordingly, the learning object abstractions and their presentation sequence which is decided based on the learning preference, intention

TABLE 3. Sequencing of the chosen abstractions of learning object based on psychology for a person coming with research intention

Type of learner	Order of Abstraction
Extrovert	Concept, Demonstration, Case Study, Simulation, Example, Detailed Concept
Introvert	Concept, Detailed Concept, Example, Simulation, Case Study, Demonstration
Sensate	Concept, Case Study, Example, Simulations, Demonstration, Detailed concept
Intuitive	Concept, Detailed Concept, Demonstration, Simulation, Example, Case Study
Feeler	Concept, Case Study, Simulation, Demonstration, Example, Detailed Concept
Thinker	Concept, Detailed Concept, Example, Demonstration, Simulation, Case Study
Judger	Concept, Example, Case Study, Simulation, Demonstration, Detailed Concept
Perceiver	Concept, Detailed Concept, Demonstration, Simulation, Case Study, Example

and psychology of the learner is actually presented in the media preferred by the learner.

The following section describes a genetic algorithm based approach for learning scheme generation which incorporates all the three levels context parameters for generating a highly customized context-aware learning content to the learner.

IV PROPOSED ALGORITHM

In this section, a genetic algorithm based learning scheme generation for context-aware e-learning is described. The algorithm uses the context structure which is described in the previous section. Prior to the description of the algorithm, the need for adopting a genetic algorithm based approach for learning scheme generation is discussed.

A. Need for Genetic Algorithm Based Approach

There are many learner context parameters considered for adaptive learning scheme generation as depicted in the newly proposed context structure given in Fig 1. These parameter values are considered as constraints to be fulfilled for learning scheme generation. In order to generate a customized learning scheme for a learner, all the context values of the learner should be satisfied. For fulfilling multiple constraints, many alternate learning schemes should be generated and evaluated in order to determine the learning scheme which best suits a learner. For constraint satisfaction problems in which multiple alternative paths have to be explored, genetic algorithm based approach is best suited. Hence, the learning scheme is generated using the genetic algorithm based approach.

The following section explains the genetic algorithm based adaptive learning scheme generation algorithm.

A. Definition of Chromosome String

The chromosome string considered here consists of 3 types of genes, such as content level genes, presentation level genes and media level genes as shown in Fig 2. The content level genes are composed of IDs of learning objects which constitute the learning path of a learner. The presentation level genes represent the order of presentation of learning objects to the learner based on his learning preference and intention.

Each learning object can be presented in six ways such as concept, example, case study, simulation, demonstration and detailed concepts. The media level genes represent the media of learning object such as audio, video or text.

B. Initial Population

The initial population is obtained by taking permutation of each set of genes.

Content Level Genes	Presentation Level Genes	Media Level Genes

Figure 2. Gene Representation

C. Selecting the Fitness Function

The fitness function is a performance index that is applied to judge the quality of generated learning schemes. Here three sets of genes mentioned above are evaluated separately for finding fitness and finally combined all the three to calculate the overall fitness (1) of the chromosome.

$$f = f(s) + f(p) + f(m) \qquad (1)$$

where f(s) denotes the content level fitness, f(p) denotes the presentation level fitness and f(m) denotes the media level fitness.
Content level fitness is calculated using (2),

$$f(s) = \left\{ \begin{array}{l} \text{Effort taken for studying} \\ \text{one learning object with respect} \\ \text{to other learning object} \end{array} \right\} * \left\{ \begin{array}{c} \text{difficulty of} \\ \text{LO going} \\ \text{to study} \end{array} \right\} \qquad (2)$$

Presentation level fitness is based on the learning preference and intention of the learner. For each learner, according to his intention, a particular order of presentation of learning object is most suitable. The deviation of the randomly generated presentation sequence from the most suitable presentation required is taken consideration and appropriate grade is given as fitness value. Presentation level fitness is calculated using (3).

$$f(p) = \Sigma \left(\begin{array}{c} \text{Position of abstraction of LO} \\ \text{in the Presentation based on} \\ \text{Psychology of Learner} \end{array} \right) \left(\begin{array}{c} \text{Position of each} \\ \text{type of LO in the} \\ \text{randomly} \\ \text{generated} \\ \text{Presentation} \end{array} \right) \qquad (3)$$

Media level fitness is calculated based on the device used by the learner, band width of the internet connection available for the device and media preference of the learner. The fitness value of each combination is given in the table 4.

TABLE 4. Media Level Fitness Table

Device	Bandwidth	Preference	Fitness Value
PDA/ Mobile	Low	Audio	0.1
,,	Low	Text	1.0
,,	Low	Video	0.1
,,	Medium	Audio	0.5
,,	Medium	Text	1.0
,,	Medium	Video	0.1
,,	High	Audio	1.0
,,	High	Text	1.0
,,	High	Video	1.0
DESKTOP /LAPTOP	Low	Audio	0.1
,,	Low	Text	0.1
,,	Low	Video	1.0
,,	Medium	Audio	0.5
,,	Medium	Text	0.5
,,	Medium	Video	1.0
,,	High	Audio	1.0
,,	High	Text	1.0
,,	High	Video	1.0

E. Reproduction Operation

In the reproduction operation, the chromosome with the larger fitness function value will have a higher probability to reproduce the next generation. The aim of this operation is to choose good chromosome to achieve the goal of gene evaluation. The reproduction operators used in this algorithm is two point crossover operator and swap mutation operator.

F. Stop Criterion

The genetic algorithm repeatedly runs the reproduction, cross over and mutation operations until it converge at maximum fitness value. The steps of the algorithm is explained Fig 3.

V THE IMPLEMENTED SYSTEM

This section introduces the system architecture which is based on the algorithm. The system architecture is shown in Fig. 4. The system includes four context tracking modules, two databases and genetic based adaptive learning scheme generation algorithm module. The following section describes briefly how the algorithm works for computer networks course. The learning object topics designed for Computer Network course, is shown in Table 4, which contains leaning object topics, their IDs, prerequisites of each learning objects and difficulty of each learning objects for studying them. Table 5 shows the effort taken for studying each learning objects with respect to other learning objects. The effort is given in such a way that the learning object which is helpful for studying other learning object is given low value. For example if learning object 2 is a pre-requisite for learning object 3, 4 etc. then difficulty value from 2 to 3, 4 etc is given as minimum. Fig. 5 shows entire layout of e-learning system. The learner registers with the system. He/she enters the details in the registration form which is shown in Fig.6. Based on the profile context, preference context, learning context and infrastructure context, the adaptive learning scheme is generated. Fig. 7 shows the generated learning scheme which is represented as a chromosome. This is given to the server to get the personalized learning materials.

1. [Start] Generate random population of chromosomes .
2. [Fitness] Evaluate the fitness f(x) of each chromosome f(x) = f(s) + f(p) + f(m)
where f(s) is content level fitness, f(p) is presentation level fitness, and f(m) is media level fitness. Refer Annexure ii
3. [New Population] Create new population by repeating following steps until the new population complete.
 1. [Selection] Select two parent chromosomes from a population according to their fitness, the better fitness, the bigger chance to be selected.
 2. [Cross over] Two point cross over the parents to form new children.

Figure 3. Genetic Algorithm based Adaptive Learning Scheme Generation Algorithm

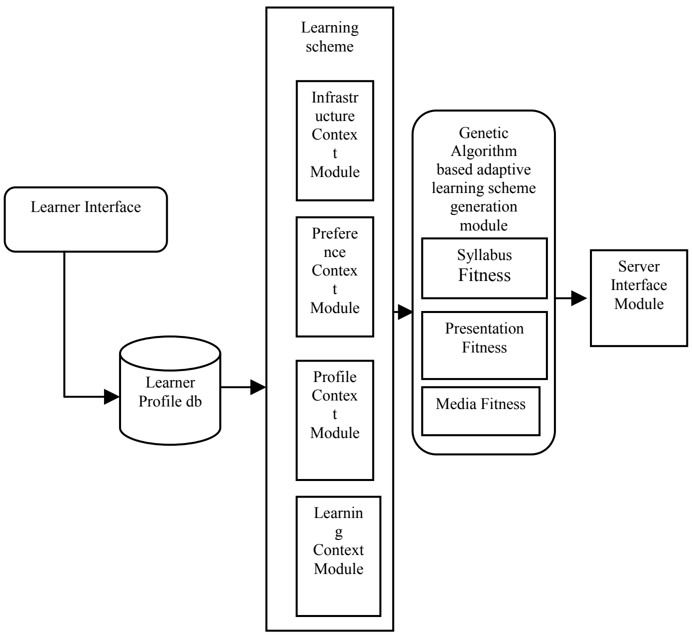

Figure 4. System Architecture

TABLE 4. The contents of the designed course material

Si No	Learning Objects	ID	Pre requisites	Difficulty
1	Network Introduction	1	-	1
2	Network Media	2	1	1
3	Network Protocol	3	1	2
4	Network Types	4	1	1
5	Network Operating System	5	1, 3, 4	3
6	Network Connection Services	6	1, 2, 3, 4	3
7	Network Administration	7	1, 2, 3, 4, 5, 6	4

TABLE 5. Effort taken for studying one Learning Objects (LO) with respect to other LO

LO ID►▼	1	2	3	4	5	6	7
1	0	0.02	0.20	0.03	0.35	0.30	0.40
2	-0.01	0	0.20	0.10	0.35	0.30	0.40
3	-0.03	-0.02	0	-0.01	0.25	0.2	0.3
4	-0.03	-0.01	0.2	0	0.35	0.3	0.4
5	-0.03	-0.02	-0.2	-0.01	0	0.2	0.4
6	-0.03	-0.02	-0.2	-0.01	-0.35	0	0.4
7	-0.03	-0.02	-0.2	-0.01	-0.35	-0.3	0

Figure 5. The User Interface of e-learning System

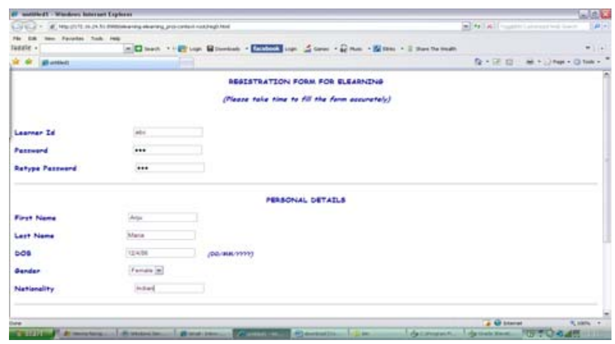

Figure 6. Registration Form

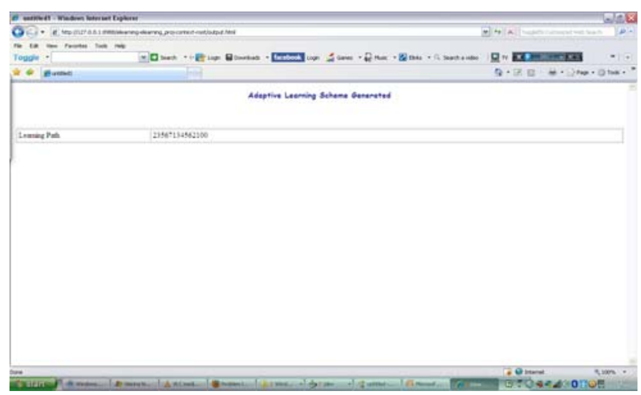

Figure 7. The generated Adaptive Learning Scheme

VI CONCLUSION

The early e-learning platforms did not include the characteristics of learner and ended up with static inflexible e-learning systems. But currently, customized e-content which adapts to learner's context is an emphatic requirement of any e-learning system.

The existing e-learning systems adapt content based on various subset of context parameters and generate customized learning paths. These algorithms do not generate the learning path based on the entire context of a learner. This is because the context structure considered by them is not complete.

In this paper, a new three level structure for learner's context comprising of the content level, presentation level and media level is defined. The learning path generation algorithm now evolves into a learning scheme generation as it generates a learning path accommodating the entire learner's context.

The learning scheme generation algorithm is designed to be genetic. This is because the various learner's context parameter values are viewed as constraints to be fulfilled in the learning scheme generation and genetic algorithms are best suitable for handling multiple constraint satisfaction problems which have many alternative solutions.

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TABLE 1. Comparison Table

Comparison parameter	Domain Modelling				Constraint Satisfaction Problem		Clustering of Users	Case Based Reasoning	Learning Profile of Previous Users	Statistical Approach	Automatic Generation Of Learning Path Algorithm	Weighted Learning Object	Petri-nets Based
	Learning path graph	Concept Map	Ontology	Learning Activity Graph	Genetic Programming	Swarm Intelligence	Neural Networks		Ant Colony	Bayesian Network			
Personal Information	N	N	N	N	N	N	N	N	N	N	N	N	N
Personality Type	N	N	N	N	N	N	N	N	N	N	N	N	N
Level of Expertise	**Y**	**Y**	**Y**	N	**Y**	N	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	N
Learning Style	**Y**	N	N	N	N	N	N	N	**Y**	**Y**	N	N	N
Learner Preference	**Y**	N	**Y**	**Y**	N	N	**Y**	N	N	N	**Y**	**Y**	N
Learner Intention	N	N	N	N	N	N	N	N	N	N	**Y**	**Y**	N
Situation	N	N	N	N	N	N	N	N	N	N	N	N	N
Network	N	N	N	N	N	N	N	N	N	N	N	N	N
Device	N	N	N	N	N	N	N	N	N	N	N	N	N
Learning Pace	N	N	N	N	N	N	**Y**	N	N	**Y**	N	N	**Y**
Learning State	N	N	N	N	N	N	N	N	N	N	N	N	**Y**
Comprehension Level	N	N	N	N	N	N	N	N	N	N	N	N	N
Constraints between Learning Object	N	N	N	N	N	**Y**	N	N	N	N	N	N	**Y**
Personalized or Grouped	Personalized	Personalized	Personalized	Personalized	Personalized	Personalized	Grouped	Personalized	Personalized	Personalized	Personalized	Personalized	Personalized