Pareto-optimal Solutions for Question paper Template Generation

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***Abstract*— Generating multiple sets of question paper for a subject examination is laborious and time consuming by manual approaches. To cope up with this problem, an enhanced approach using Pareto-optimal solution is proposed. This approach designs multiple Question Paper Templates which can be used as standards in generating multiple sets of question papers. Experimental result shows that the proposed algorithm performs better than the existing evolutionary approach for generating multiple question papers with proportionate topic coverage as well as proportionate coverage of cognitive levels of educational taxonomy.**

Keywords*— *Pareto-optimal evolutionary algorithm; cognitive levels; question paper generation; question paper template

I. Introduction

Question paper generation for every subject of a course by the concerned instructor is considered as a hot issue in e-assessment systems. Lately there are many research papers that apply variety of algorithms such as machine learning [1], evolutionary algorithms [2][3], particle swarm optimization [4] etc., to solve automated question paper generation problems. Among these algorithms, evolutionary algorithms have been widely used for question paper generation due to its extensive adaptability. However, these evolutionary algorithms are found not efficient with respect to time for meeting multi-constraints specified by an instructor for generating multiple question papers. In order to overcome this limitation, an enhanced approach using Pareto-optimal solution is proposed**.** This algorithm is found to generate optimal Question Paper Template (QPT) in lesser time. These QPTs can be used to generate multiple question papers with non-overlapping questions. Multiple question paper generation is considered as a requirement in the current university based examination system. This requirement is important as the generated question papers can be used at different times due to the discrepancy in the conduct of an examination or failure of students at the regular examination or occurrence of any other unexpected events.

We have proposed a Pareto-optimal based intelligent evolutionary algorithm which is better than the existing evolutionary approaches. This newly designed algorithm generates multiple QPTs that satisfy instructor specified multi-constraints. The proposed approach outperforms many of the existing approaches [5] in terms of the amount of time needed for designing QPTs and also using them as standards for selecting non-overlapping questions for question paper generation. This is achieved by performing enhancements to the working of an evolutionary algorithm. Most of the existing evolutionary algorithm based question paper generation systems follow an iterative method for question selection. Iterative process starts by randomly creating a population of individuals (set of questions), performing search and selection of the required individual by matching the fitness function, allowing iterative process to continue by applying recombination operations and finally terminating the process after the user specified number of iterations or after achieving the desired solutions. This random approach of selecting a set of questions encountered long and indefinite time delay. Our enhanced evolutionary approach known as Pareto-optimal based evolutionary algorithm introduces a new method of question selection by designing multiple QPTs. Each of these designed QPTs can act as a standard in generating a question paper by performing an intelligent search of questions based on the designed QPT. The approach that can be used to search non-overlapping questions for multiple question paper generation is out of the scope of this paper and is being addressed in an independent paper. This paper is structured as follows - Section 2 describes the background and related work, Section 3 discusses about Pareto-optimal based evolutionary algorithm. Section 4 generalizes the goals to be taken in to account while designing evolutionary multi-objective approaches. Section 5 includes the problem description. Section 6 discusses a real life case study to test the proposed approach. Finally section 7 concludes the paper.

II. Background and Related Work

Research carried out in this field indicates that a well-constructed question paper helps in evaluating the learning achievements of students [6][7][8]. Generation of multiple question paper sets that meet multiple assessment criteria can be efficiently achieved by designing a question paper template meeting multiple criteria and use it as a standard in question paper generation [9]. In [9], we designed dynamic templates that meet multiple constraints by applying evolutionary programming. Different criteria

978-1-4673-6217-7/13/$31.00 ©2013 IEEE

that were considered for designing QPTs were - Maximum marks (M), distribution of topic weights (t_1, t_2,...,t_m), distribution of cognitive levels weights based on blooms taxonomy (l_1,l_2,…,l_n) etc.,. Our evolutionary program randomly assigned the topic-level weights, tlw_{11}, tlw_{12}, tlw_{ij},…, tlw_{mn} which is the weight allotted to a particular cell of a template. Table 1 shows the format of QPTs generated using our evolutionary programming approach.

TABLE I. QPT FORMAT

topic /level	**level 1**	**level 2**	**…**	**level n**	**topic weight**
topic 1	tlw_{11}	tlw_{12}	…	tlw_{1n}	t_1
topic 2	tlw_{21}	tlw_{22}	…	tlw_{2n}	t_2
…	…	…	…	…	…
topic m	tlw_{m1}	tlw_{m2}	…	tlw_{mn}	t_m
level weight	l_1	l_2	…	l_n	M

These evolutionary programming based templates had a major disadvantage that they used a randomized approach for assigning the topic-level-weights. Even though it generated populations of question paper templates iteratively, many of them were not adequate in terms of its fitness. During the iterative population generation, significant runtime delay was observed. This is due to the wastage of time in searching a set of random topic-level-weights that satisfied both topic weights and level weights. Also, this evolutionary programming approach never guaranteed the generation of the instructor specified number of templates even after running it for the instructor specified number of iterations. In order to overcome these limitations of evolutionary programming, we have proposed a Pareto-optimal based evolutionary algorithm that aims to find a set of optimal tradeoff solutions known as the Pareto optimal set [5]. The class of evolutionary algorithms which approximate Pareto set is known as Evolutionary Multi-Objective Optimization Algorithm (EMOOA). A notion in EMOOA is to provide the decision-maker with a set of Pareto optimal solutions, which are not dominated by any other solutions [5].

III. SIGNIFICANCE OF PARETO-OPTIMAL SOLUTIONS

MOOA has S objective functions f(x) = (f1(x), f2 (x), …, ft (x))^s , each of them either can be minimized or maximized. The biggest difference between single and multi-objective algorithms is that in multi-objective optimization, the objective functions constitute a multi-dimensional space. When conflicting multi-objective criteria are included in the MOOA, it results in Pareto-optimal solutions. If none of the two compared solutions dominates each other, these solutions are called non-dominated solutions or Pareto-optimal solutions. At present there is a good amount of research work that proposes the use of Pareto-optimal approaches in solving multi-objective problems such as the travelling salesman problem, assignment problems, shortest path problems etc [5].

IV. GOALS IN EMOOA

An evolutionary algorithm is initiated on a set of candidate solutions that are subsequently modified by two basic operators: *selection* and *mutation*. Selection is in charge of applying the fitness function and choosing candidate solutions satisfying these fitness conditions, while recombination results in maintaining diversity among solutions. Two goals have to be taken into account while designing a multi-objective evolutionary algorithm which are listed below –

1) Guiding the search towards the Pareto set
2) Keeping a diverse set of non-dominated solutions

The first goal is mainly related to assigning scalar fitness values in the presence of multiple objectives. The second goal concerns generation of diverse candidate solutions.

In contrast to single-objective optimization [10][11][12], where objective function and fitness function are directly and easily related, in multi-objective optimization fitness assignment and selection have to take into account all the different objectives [13]. Among the different fitness assignment strategies, the most commonly used are those based on aggregation [5]. This approach, which mimics the weighted-sum method, aggregates the objectives into a single parameterized objective function. The parameters of this function are systematically varied during the optimization run in order to find a set of non-dominated solutions instead of a single trade-off solution.

In our EMOOA, we apply the weighted sum method to optimize the two objectives such as- the percentage of coverage assigned to topic weights and also the percentage of importance assigned to taxonomy level weights. Our aggregate function applies two different weights independently to these objectives and generates a single parameterized objective function equivalent to these two objectives.

V. PROBLEM FORMULATION

A. Problem Description for designing QPTs includes the following –

1) Generate Population of QPT: Q different question paper templates as specified by instructor/paper setter are either generated at initialization or at successive iterations to form a population. The set of templates of the initial population is formed by calculating the topic-level-weights of each cell using the formula- $tlw_{mn} = (t_m * l_n) / M$ and adjusting them to its nearest integer values.

2) Calculate Fitness of QPT: Calculate fitness of QPTs using the fitness function, F. Details of Fitness (F) calculation is explained in section B.

3) Selection: Apply selection operation to the generated QPT's. It is carried out based on the criteria that the set of

QPT's with fitness value in the range of 0.8-1.0, are to be identified and selected.

4) Mutation: Among the selected QPTs, identify the ones that can be mutated to increase its fitness value. Perform mutation on these identified templates by changing the topic-level weight of any cell and accordingly adjusting all the rest of the cell values.

5) Termination: step 1 till step 4 is repeated iteratively until optimal solution is found or the instructor specified number of iterations is completed (whichever is earlier).

B. Problem formulation

1) Input for QPT generation

a. M = Total marks allotted for designing QPTs.
b. $T=<t_1, t_2,...,t_m>$, the vector of selected topic weights where t_i is the weight assigned to the i^{th} topic.
c. $L=<l_1,l_2,\ldots,l_n>$, the vector of selected cognitive level weights of educational taxonomy where l_j is the weight assigned to the j^{th} cognitive level .

2) Problem Statement

The problem is to assign topic-level-weights, $T=< tlw_{11}, tlw_{12}, tlw_{ij},\ldots, tlw_{mn} >$, so as to get the optimum value for the fitness function (F). Let x_1 be the percentage of importance assigned to topic coverage and let x_2 be the percentage of importance assigned to taxonomy level coverage. In order to define fitness, we have defined the following terms-

a. The weakness of a topic (WTi):

For a topic i, $WTi=\sum_{j=1}^{n} tlw_{ij}$ (1)

b. The topic wise fitness(Ftopic):

$F_{topic}=\sum_{i=1}^{m} WTi/M$ (2)

c. The weakness of a level (WLj):

For a level j, $WLj=\sum_{i=1}^{m} tlw_{ij}$ (3)

d. The level wise fitness(Flevel):

$F_{level}=\sum_{j=1}^{n} WTj/M$ (4)

e. The overall fitness(F), of the template:

$$F = (x_1 * F_{topic} + x_2 * Flevel) / (x_1 + x_2) \quad (5)$$

3) Output displaying QPTs

Instructor specified Q number of QPTs satisfying the fitness function F or the set of QPTs generated before the termination condition of instructor specified number of iterations.

VI. Experimental Results

Using the real data of our university examination system, we generated multiple QPT's for the subject of Software Engineering (SE) offered at the third year of the three year bachelor's degree course of computer science (B.Sc Computer Science) at our University. Cognitive levels of Bloom's Taxonomy were considered.

A. Input

1) Total marks= 50
2) Selected topic weights =05, 15, 15, 15
3) Selected level weights = 15,15,05,15
4) Population size=10
5) Mutation rate=0.01
6) Paper Setter Specified Number of iterations=50
7) percentage of importance assigned to topic coverage=0.50
8) percentage of importance assigned to taxonomy level coverage =0.50
9) Expected number of QPT's=3

B. Output

SE QPT_1 in Table II, SE QPT_2 in Table III and QPT_3 in Table IV below shows the three different samples of generated QPT's for SE. Generation of these QPT's were successful within 50 iterations.

TABLE II. SE QPT_1

topic /level	know	under	appl	anal	topic weight
Fact finding	2	1	1	1	05
Sys. Anal	4	5	1	5	15
Sys. design	5	4	1	5	15
Sys. coding	4	5	2	4	15
Level weight	15	15	5	15	50

TABLE III. SE QPT_2

topic /level	know	under	appl	anal	topic weight
Fact finding	1	2	1	1	05
Sys. Anal	5	4	2	4	15
Sys. design	4	5	1	5	15
Sys. coding	5	4	1	5	15
Level weight	15	15	5	15	50

TABLE IV. SE QPT_3

topic /level	know	under	appl	anal	topic weight
Fact finding	1	1	1	2	05
Sys. Anal	5	5	1	4	15
Sys. design	5	5	1	4	15
Sys. coding	4	4	2	5	15
Level weight	15	15	5	15	50

TABLE V. PERFORMANCE ANALYSIS

Evolutionary Programming			Pareto-Optimal Based Evolutionary Algorithm		
templ_no	itearion	fitness	templ_no	iteration	fitness
$t_{1,1}$	1	0.5001	$t_{1,1}$	1	0.7045
$t_{1,2}$	1	0.6012	$t_{1,2}$	1	0.7066
$t_{1,3}$	1	0.6034	$t_{1,3}$	1	0.7077
$t_{1,4}$	1	0.5075	$t_{1,4}$	1	0.7079
$t_{1,5}$	1	0.5011	$t_{1,5}$	1	0.7093
$t_{1,6}$	1	0.5113	$t_{1,6}$	1	0.7108
$t_{1,7}$	1	0.6133	$t_{1,7}$	1	0.7127
$t_{1,8}$	1	0.6035	$t_{1,8}$	1	0.7149
$t_{1,9}$	1	0.5149	$t_{1,9}$	1	0.7158
$t_{1,10}$	1	0.6194	$t_{1,10}$	1	0.7198
$t_{2,1}$	2	0.6204	$t_{2,1}$	2	0.7202
$i_{2,2}$	2	0.6253	$i_{2,2}$	2	0.7209
.	.	.	.	.	.
$t_{3,1}$	3	0.7275	$t_{3,1}$	3	0.8223
.	.	.	.	.	.
$t_{4,1}$	4	0.5254	$t_{4,1}$	4	0.8291
.	.	.	.	.	.
$t_{28,1}$	28	0.5703	$t_{28,1}$	28	0.8717
$t_{28,2}$	28	0.5316	$t_{28,2}$	28	0.8726
.	.	.	.	.	.
$t_{32,1}$	32	0.6102	$t_{32,1}$	32	0.9109
$t_{32,2}$	32	0.6132	$t_{32,2}$	32	0.9113
.	.	.	.	.	.
$t_{34,1}$	34	0.5345	$t_{34,1}$	34	0.9313
$t_{34,2}$	34	0.7399	$t_{34,2}$	34	0.9326
.	.	.	.	.	.
$t_{40,1}$	40	0.6798	$t_{40,1}$	40	0.9971
$t_{40,2}$	40	0.6654	$t_{40,2}$	40	0.9988
$t_{40,2}$	40	0.5432	$t_{40,2}$	40	0.9997
$t_{45,1}$	45	0.7111	$t_{45,1}$	45	terminated
$t_{45,2}$	45	0..5431	$t_{45,2}$	45	terminated
.	.	.	.	.	.
$t_{50,9}$	50	0.6001	$t_{50,9}$	50	terminated
$t_{50,10}$	50	0.5998	$t_{50,10}$	50	terminated

C. Performance Analysis

Table V shows the experimental results obtained after iteratively generating the instructor specified number of three SE QPTs. Performance comparison of the proposed Pareto-optimal based evolutionary algorithm is done with the already implemented evolutionary programming approach. Results indicate that the Pareto-optimal solutions were achieved at the 40th iteration, whereas the evolutionary programming approach failed to generate optimal solutions even after 50 iterations. The algorithm terminated after 50 iterations.

VII. CONCLUSION

A new approach for generating multiple set of question papers using QPT's has been discussed. QPT's were successfully generated using Pareto-optimal based evolutionary algorithm. The primary objective of this study was to generate multiple QPT's, satisfying the instructor specified multi-constraints. The main advantage of this new approach as compared to our previous evolutionary programming approach is that the runtime delay of the previous approach is significantly reduced by avoiding randomized approach for population generation. Complexity of this template generation algorithm is proportional to the number of topics, the number of levels and the rate of mutation. This new approach is very important in situations where instructors wish to generate multiple set of question papers in a subject for the same examination. Examinations such as in-semester, end-semester etc., forces the proportionate coverage of topics and cognitive levels. Using multiple QPT's, there are lesser probabilities of similar questions getting automatically extracted during the question selection process. Our future work will focus on designing algorithms for automatic question paper generation with minimal overlapping questions.

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