Evaluation of Hyper-Heuristic Method Using Random-Hill Climbing Algorithm in the Examination Timetabling Problem

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Abstract. Examination timetabling is included in the category of Nondeterministic Polynomial-Hard (NP-Hard) problems, namely problems that cannot be solved by conventional methods in finding optimal solutions. One solution to this problem is to use the Simple Random - Hill Climbing - Hyper Heuristic (SR-HC-HH) approach. But this approach still cannot produce an optimum solution. The researcher presents a critical analysis of the performance evaluation of the solution method used. The stages of this research include: (1) problem identification; (2) literature study; (3) data retrieval and understanding; (4) translation of mathematical models into data structures; (5) evaluation of the SR-HC-HH algorithm; (6) trial implementation; (7) algorithmic experiment parameters; and (8) analysis of results and conclusions. SR-HC-HH algorithm used in Hyper-Heuristics-based applications is able to solve timetabling problems in the Examination Timetabling Problem domain in the ITC-2007 dataset, but it is still not optimal. Parameters that can be changed in this study are the number of iterations (time limit) and algorithms for selection of Low Level Heuristics. Changing parameters in the trial scenario can also affect the results of a more optimum solution. The parameters to be explored in this study include LLH selection strategies and move acceptance in hyper-heuristics.

Keywords : Examination Timetabling Problem, Hill Climbing , Hyper-Heuristic, ITC 2007, Simple Random.

1. Introduction

Timetabling problems are problems that involve four parameters namely limited time (T), limited resources (R), limited meetings (M), limited constraints (C). The problem is to determine the time and resources at the meeting so that the constraints are met [1]. Theoretically, exam timetabling is a NP-complete problem [2] [3] [4] [5] where there is no algorithm that is really able to solve this problem in a non-polynomial timeframe. This timetabling problem is formulated in a variety of datasets. The Carter and ITC 2007 dataset is one of the benchmarks used to represent exam timetabling problems. But the difference between the two is that the 2007 ITC dataset offers a much more complex representation of timetabling problems in the real world [5].

The state-of-the-art of this problem generally uses the meta-heuristic method. However, this method has several drawbacks including the need for tuning parameters and knowledge of specific problem domains. So it will be very difficult if the dataset has changed from time to time. Problem knowledge is very difficult to generalize, applying metaheuristics to new problem domains is also not easy, this is the basis why metaheuristics need to be developed further if you want to apply them to different problem domains [6].
The automatic heuristic design emerged as an efficient way to improve the performance of search algorithms by adjusting parameters and operators in an online manner [6]. Hyper-heuristic is an example of this methodology. Hyper-heuristic is a search method that solves optimization problems by exploring the search space of a given heuristic series. One of the main concepts is to solve various kinds of problems (cross-domain) by making it general. The advantage of hyper-heuristic itself is the ease in generalizing different domain problems.

In this study evaluates the Simple Random - Hill Climbing - Hyper Heuristic (SR-HC-HH) algorithm. Based on previous studies, further development of the Hyper-Heuristic approach is needed. Therefore this study evaluates the Simple Random algorithm as a selection strategy and Hill Climbing as a Move Acceptance (MA) hyper-heuristic for exam timetabling problems and testing it on the 2007 ITC dataset (Examination Timetabling Problem). In addition, in this study an analysis of the performance of the SR-HC-HH algorithm on exam timetabling problems.

2. Related Works

Muklason, 2017 developed a new modeling of exam timetabling problems, which previously only used a single objective, then developed into a multi-objective [5]. This study examines the problem of exam timetabling with a hyper-heuristic approach using the HyFlex framework. The purpose of this study is to investigate the structure of exam timetabling problems in the real world, critical issues, as well as aspects of current exam timetabling issues, specifically the issue of justice and then make it a new formulation of exam timetabling problems. The algorithm used in the LLH selection strategy is the Self-Adaptive Learning algorithm, while for move acceptance uses the Great Deluge algorithm. Then tested on the Carter dataset, ITC 2007, Yeditepe, and Nott. The main contribution of this research is the Hyflex improved framework, by adding exam timetabling problems as a new problem domain and adding Self-adaptive (SA) algorithms as LLH selection strategies and Great Deluge (GD) as move acceptance. And the results show that this new strategy is able to compete with the strategies used by previous researchers.

T. Müller, 2009 developed a solver to deal with exam timetabling problem [7]. The algorithm used is Iterative Forward Search (IFS) in the construction phase and uses three algorithms in the optimization phase namely Hill Climbing (HC), Great Deluge (GD), Annealing Simulation (SA). Demeester, 2012 also developed an exam timetabling solver. There are three algorithms used in the hyper-heuristic optimization stage namely Annealing Simulation (SA), Great Deluge (GD), and Late Acceptance (LA) [8]. S. A. Rahman, 2014 uses an adaptive linear combination approach for exam timetabling problems [9]. M. Alzaqebah, 2014 uses artificial bee colony and late-acceptance hill-climbing algorithms to solve exam timetabling problems [10]. E. K. Burke, 2014 uses the Adaptive Improvement Hyper-heuristic (AIH) algorithm to complete the exam timetabling problem [11].

Battistutta, 2015 uses the Simulated Annealing (SA) approach tuned for exam timetabling problem [12]. Doerr, 2018 evaluated the performance of the Adaptive Random Gradient (ARG) algorithm on a hyper-heuristic approach [13]. Kheiri, 2016 uses an Iterated Multi-stage selection Hyper-heuristic on six different problem domains [14]. M Cheraitia, 2016 using a simple graph colouring heuristic and Simulated Annealing is then used as an iterative heuristic for improving the spreading of the conflicting exams [15].

Pillay, 2014 provides an overview and critical analysis of hyper-heuristics for educational timetabling and proposes future research directions, focusing on using hyper-heuristics to provide a generalized solution to educational timetabling [16]. Soria-Alcaraz, 2016 introduce an ILS approach, strengthened by a hyper-heuristic which generates heuristics based on a fixed number of add and delete operations. The performance of the proposed hyper-heuristic is tested across two different problem domains using the real-world benchmark of course timetabling instances from the second International Timetabling Competition Tracks two and three [17].

Tanzila Islam, 2016 analyze that the Tabu Search technique is an essential method for getting a feasible solution. In this paper, we describe how Tabu Search works and how to get a feasible solution by using this algorithm [18]. Woumans, 2016 use approaches the Examination-Timetabling Problem
(ETP) from a student-centric point of view and propose two Column Generation (CG) algorithms [19]. Zamli, 2017 describes the experience with four hyper-heuristic selection and acceptance mechanisms namely Exponential Monte Carlo with counter (EMCQ), Choice Function (CF), Improvement Selection Rules (ISR), and newly developed Fuzzy Inference Selection (FIS), using the t-way test generation problem as a case study [20].

3. Methods

Method used in the study is indicated by the research flow, namely: (1) problem identification; (2) literature review; (3) data retrieval and understanding; (4) translation of mathematical models into data structures; (5) evaluation of the SR-HC-HH algorithm; (6) trial implementation; (7) algorithmic experiment parameters; and (8) analysis of results and conclusions. Details of this research method, can be seen in Figure 1

![Research Flow](image)

*Figure 1. Research Flow*
4. Results and Discussions

The following results compare the SR-HC-HH algorithm with the algorithm in the literature.

Table 1. Comparison of ITC-2007 Dataset Experiment Results

| NO | INSTANCES | SR-HC-HH | MUKLASON 2017 | MULLER 2009 [7] | DEMEESTER 2012 [8] | RAHMAN 2014 [9] | ALZAEQ BAH 2014 [10] | BURKE 2014 [12] |
|----|-----------|---------|---------------|----------------|-------------------|----------------|---------------------|-----------------|
|    |           |         | MUKLASON       |                |                   |                |                     |                 |
|    |           |         | 2007           |                |                   |                |                     |                 |
|    |           |         | SR-HG-HH       |                |                   |                |                     |                 |
|    |           |         | RL-HG-HH       |                |                   |                |                     |                 |
|    |           |         | SA-HG-HH       |                |                   |                |                     |                 |
|    |           |         |                | MUKLASON 701   | 4370             | 6060           | 5231                | 5328            |
|    |           |         |                |                  |                  |                |                     |                 |
| 1  | EXAM 1    | NA      | 6579           | 9               | 5809              | 4370           | 6060                | 5231            |
|    |           |         |                |                  |                  | 400             | 515                 | 433             |
| 2  | EXAM 2    | 40252   | 584            | 535             | 490               | 1081           | 10049               | 9265            |
|    |           |         |                |                  |                  | 1115           | 23580               | 10178           |
|    |           |         |                |                  |                  |                |                     |                 |
| 3  | EXAM 3    | 100582  | 3              | 92              | 9                 | 1323           | 10049               | 2               |
|    |           |         |                |                  |                  | 219            | 1410                | 3510            |
| 4  | EXAM 4    | NA      | 3              | 92              | 0                 | 18141          | NA                  | 17787           |
|    |           |         |                |                  |                  |                |                     |                 |
| 5  | EXAM 5    | 127245  | 3658           | 0               | 3596              | 2988           | 4855                | 3083            |
|    |           |         |                |                  |                  | 281            | 2607                | 3624            |
|    |           |         |                |                  |                  |                |                     |                 |
| 6  | EXAM 6    | 52790   | 5              | 30              | 5                 | 26950          | 27605               | 26206           |
|    |           |         |                |                  |                  | 515            | 26060               | 26240           |
| 7  | EXAM 7    | 65737   | 5145           | 1               | 5185              | 4213           | 6065                | 10712           |
|    |           |         |                |                  |                  | 114            | 4562                | 2               |
|    |           |         |                |                  |                  |                |                     |                 |
| 8  | EXAM 8    | 130394  | 9348           | 05              | 9180              | 7861           | 9038                | 8043            |
|    |           |         |                |                  |                  | 138            | 12713               | 4               |
|    |           |         |                |                  |                  |                |                     |                 |
| 9  | EXAM 9    | NA      | 1074           | 2               | 1032              | 1047           | 1184                | 1111            |
|    |           |         |                |                  |                  | 155            | 1443                | NA              |
|    |           |         |                |                  |                  |                |                     |                 |
| 10 | EXAM 10   | NA      | 1              | 73              | 8                 | 16682          | 15561               | 14825           |
|    |           |         |                |                  |                  | 344            | 3360                | NA              |
|    |           |         |                |                  |                  |                |                     |                 |
| 11 | EXAM 11   | NA      | 5              | 62              | 7                 | 34129          | NA                  | 28891           |
|    |           |         |                |                  |                  | 701            | NA                  | NA              |
| 12 | EXAM 12   | NA      | 5163           | 3               | 5202              | 5535           | 5483                | 6181            |

The experimental results above show that the red one is a more optimal solution than the others. SR-HC-HH algorithm used in Hyper-Heuristics-based applications is able to solve timetabling problems in the Examination Timetabling Problem domain in the ITC-2007 dataset, but it is still not optimal. Even the previous researchers also have not found optimal results for all instances in the dataset. Some adjustments are needed in the future so that the results are more optimum and able to outperform all the algorithms used by previous researchers.

Parameters that can be changed in this study are the number of iterations (time limit) and algorithms for selection of Low Level Heuristics. Changing parameters in the trial scenario can also affect the results of a more optimum solution.

5. Conclusions and Future Works

Simple algorithm used in applications that have been developed that is Simple Random - Hill Climbing based on Hyper-Heuristics is able to solve timetabling problems in the Examination Timetabling Problem domain in the ITC-2007 dataset, but it is still not optimal. Even the previous researchers also have not found optimal results for all instances in the dataset. Some adjustments are needed in the future so that the results are more optimum and able to outperform all the algorithms used by previous researchers. Changing parameters in the trial scenario can also affect the results of a more optimum solution. Parameters that can be changed in this study are the number of iterations (time limit) and algorithms for selection of Low Level Heuristics.
It can be said that the problem faced when conducting experiments with the ITC2007 dataset is the establishment of an initial solution that exceeds the time limit and the output produces an error message. Therefore, the research development that will be carried out is about the initial solution that must be improved so that it can run well and the optimization process that will produce a decent output. The parameters to be explored in this study include the number of iterations in terms of the number of running trials and the amount of time limit used. Besides the number of iterations, other parameters that will be stunning are LLH selection strategies and move acceptance in hyper-heuristics.

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