



UNIVERSITI PUTRA MALAYSIA

**TOLERABLE CONSTRUCTIVE GRAPH-BASED HYPER-HEURISTIC
ALGORITHM FOR EXAMINATION TIMETABLING**

**SHAHMZAD MOHAMMAD POUR
FSKTM 2009 11**

**TOLERABLE CONSTRUCTIVE GRAPH-BASED HYPER-HEURISTIC
ALGORITHM FOR EXAMINATION TIMETABLING**

By

SHHRZAD MOHAMMAD POUR

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in
Fulfilment of the Requirements for the Degree of Master of Science**

October 2009



To

Whom made me think



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirements for the degree of Master of Science

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October 2009

Chairman: Abu bakar Md Sultan, PhD

Faculty: Computer Science and Information Technology

Examination Timetabling Problem (ETTP) is an NP-hard typical optimization problem faced by institutions and universities across the world. This nature leads to heuristic methods cover a large branch of researches in this area. On the other hand, the problem varies from one institution to another, depending on the size, structure and constraints of that institution. Therefore generality of the proposed methods is one of the major goals in solving timetabling problem nowadays. These methods are trying to keep generality while adding to factors of these methods. Hyperheuristic is one of these approaches which make the basis of this thesis.

In heuristic approaches getting stuck in local optimum is one of the propounded problems from early days. The main cause for the local optimal problem is that heuristic algorithms either focus on exploration (global improvement) rather than exploitation (local improvement) or vice versa.



The proposal to address the mentioned problem in this thesis is an extension to constructive Graph-based Hyperheuristic (GHH) algorithm presented in (Burke et al., 2007), where the researchers have not considered a dynamic hybridization of graph-based heuristics in their framework such that each low level heuristic is applied for scheduling fixed number of examinations for construction a solution (timetable) at each step. On the other hand, no supervision exists on manner of current heuristic on the solution such that it isn't clear scheduling of each exam based on order of current heuristic leads to improving or destroying the solution. By this way there is no legal control between exploration and exploitation of the search space in order to avoid getting stuck in local optimum. This study aims to use a dynamic mechanism so that algorithm makes a balance between exploration and exploitation of graph-based heuristic search space while keep the generality of the hyperheuristic approach.

In this study a new dynamic algorithm called Tolerable Graph-based Hyperheuristic (TGHH) is proposed with a new partial evaluation function and two embedded parameters; so that new partial evaluation function is designed to evaluate partial solution at each step in order to guide algorithm scheduling per exam with current heuristic is improving or destroying the solution. Good Tolerance parameter is introduced to control exploitation of heuristic search space and Bad Tolerance to balance exploration based on partial evaluation function value at each step.

The proposed algorithm has been tested on eight of benchmark datasets introduced by (Carter, Laporte and Lee, 1996). Different pair permutations of Tolerance parameters



have been tuned in the algorithm and best pair is determined. The obtained results on five of the datasets are better than reported results by GHH presented in (Burke et al., 2007) and are in the range of published results by GHH on remained datasets. Obtaining solutions with less cost function implies previous results of other approaches were getting stuck in local optimum because now a solution has been achieved in another search space area with less violation of soft constraint that is closer to global optimum rather than previous results.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

**ALGORITMA KETAHANAN HIPERHEURISTIK BERASAKAN GRAF
KONSTRUKTIF UNTUK PENJADUALAN PEPERIKSAAN**

Oleh

SHAHZRAD MOHAMMAD POUR

Oktober 2009

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Masalah penjadualan peperiksaan (ETTP) adalah masalah pengoptimuman NP-Hard tipikal yang dihadapi oleh institusi dan universiti seluruh dunia. Situasi ini mencetuskan kaedah heuristik yang merangkumi cabang yang luas kepada masalah ini. Selain itu masalah penjadualan ini berbeza setiap institusi bergantung kepada saiz, struktur dan kekangan. Oleh itu ciri-ciri generaliti kaedah yang ditawarkan adalah merupakan matlamat utama kepada penyelesaian masalah penjadualan hari ini. Metod-metod ini cuba mengekalkan generaliti disebalik penambahan faktor-faktor ke atasnya. Hiperheuristik adalah salah satu kaedah sebegini yang menjadi asas utama tesis ini.

Terperangkap dalam optima awalan merupakan masalah utama pendekatan heuristik semenjak ianya diperkenalkan. Punca utamanya kerana algoritma berasaskan tempatan samada memokus kepada penerokaan (peningkatan global) atau pemecahan (peningkatan local) atau sebaliknya.



Proposal terhadap masalah di atas dalam tesis ini adalah lanjutan daripada Constructive Graph-based Hyperheuristic Framework oleh (Burke et al., 2007), dimana penyelidik tidak melihat kepada kacukan dinamik antara heuristik berasaskan graf dalam rangka kerja mereka seperti setiap heuristik aras bawah digunakan untuk menjadual bilangan peperiksaan tertentu bagi membina penyelesaian di setiap peringkat. Di sebahagian lain pula, tiada kewujudan kawalan kepada heuristik semasa atas penyelesaian yang mencetuskan peningkatan atau penghapusan penyelesaian. Melalui cara ini tiada kawalan sah antara penerokaan dan pemecahan ruang carian bagi mengelakkan terperangkap dalam optima awalan. Kajian ini bermatlamat menggunakan mekanisma dinamik yang membolehkan algoritma membuat imbalan antara penerokaan dan pemecahan ruang carian berasaskan graf semasa mengekalkan genelaliti kaedah hiperheuristik.

Dalam kajian ini algoritma dinamik baru dipanggil Algoritma Ketahanan Hiperheuristik berasaskan Graf (TGHH) diperkenalkan dengan satu fungsi penilaian separa dan dua umpukan parameter; jadi fungsi penilaian separa ini direkabentuk untuk menilai penyelesaian separa pada setiap peringkat bagi memandu algoritma penjadualan dengan heuristik semasa agar penyelesaian dipertingkatkan atau dihapuskan. Parameter Ketahanan baik diperkenalkan untuk mengawal pemecahan ruang carian heuristik dan ketahanan buruk pula mengimbang penerokaan berasaskan nilai fungsi penilaian separa di setiap peringkat.

Algoritma yang diperkenalkan telah diuji kepada lapan set data yang diperkenalkan (Carter, Laporte dan Lee, 1996). Pasangan permutasi kepada parameter-parameter kebolehtahanan ditala dalam algoritma dan keputusannya dibincangkan. Keputusan yang dilaporkan adalah dalam julat yang hampir sama diperolehi oleh algoritma terkini dan sebahagian keputusan dari set data adalah lebih baik dari yang dihasilkan oleh GHH seperti dilaporkan dalam (Burke et al., 2007) dan dalam julat keputusan oleh GHH bagi set data yang selebihnya. Dapatan dari penyelesaian ini dengan fungsi kos yang rendah menunjukkan keputusan dari kaedah sebelum telah tersekat dalam masalah optima setempat kerana tiada penyelesaian dicapai dalam ruang carian yang lain dengan pelanggaran kekangan rendah yang kecil menghampiri optima global.

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APPROVAL

I certify that an Examination Committee has met on **date of viva** to conduct the final examination of **Shahrzad Mohammad Pour** on her **Master of Science** thesis entitled "**TOLERABLE CONSTRUCTIVE GRAPH-BASED HYPER-HEURISTIC ALGORITHM FOR EXAMINATION TIMETABLING**" in accordance with Universiti Pertanian Malaysia (Higher Degree) Act 1980 and Universiti Pertanian Malaysia (Higher Degree) Regulations 1981. The Committee recommends that the candidate be awarded the relevant degree. Members of the Examination Committee are as follows:

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DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UPM or other institutions.

Shahzad Mohammad Pour
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LIST OF ABBREVIATIONS

ETTP	Examination Timetabling Problem
NP	Nondeterministic Polynomial-time
GHH	Graph-based Hyper-Heuristic
CLP	Constraints Logic Programming
TS	Tabu Search
SA	Simulated Annealing
HC	Hill Climbing
EA	Evolutionary Algorithms
GA	Genetic Algorithm
GHH	Graph-based Hyperheuristic
TGHH	Tolerable Graph-based Hyperheuristic
SD	Saturation Degree
LD	Largest Degree
LWD	Largest Weighted Degree
LE	Largest Enrolment
CD	Color Degree
CBR	Case-Based Reasoning



CHAPTER 1

INTRODUCTION

1.1 Background

Examination timetabling problem (ETTP) as a subclass of educational timetabling is one of the most famous problems which has taken a lot of efforts by researchers to solve it until now. At least once a year, schools and universities have to solve an instance of the timetabling problem whose manual solution requires a lot of manpower. It would be desirable to have a program that schedules courses and/or exams instead of a human.

On the other hand, the problem varies from one institution to another depending on the size, constraints, type of the problem and their objectives. It can be inferred that the solution which is appropriate for one institution, may not work at others. Therefore, the generality of the proposed methods is one of the major goals in solving timetabling problems.

On the other hand, many real-life problems lead naturally to combinatorial search which is a very computationally intensive task. Unfortunately, no general method exists for solving this kind of problems efficiently. The Automated construction of Examination timetables is a typical combinatorial optimization known as NP (Nondeterministic Polynomial-time) hard problem due to large-scale computationally, multi-constrained and belonging to combinatorial optimization. There is no linear exact method to solve the problems which fall under this category of combinatorial optimization. Of course



constructing of an initial solution (timetable) is not problem, the issue is improvement of solutions and obtaining an optimum solution.

Due to NP-hard nature of ETTP and more generally educational timetabling problem, the heuristic methods cover a large branch of researches in this area. In computer science, a heuristic algorithm or simply a heuristic is an algorithm that ignores whether the solution to the problem can be proven to be correct, but which usually produces a good solution or solves a simpler problem that contains or intersects with the solution of the more complex problem. Heuristics are typically used when there is no known way to find an optimal solution, or when it is desirable to give up finding the optimal solution for an improvement in run time (Pearl and Judea, 1984).

In search algorithms two conflicting aspects are termed 'exploration' and 'exploitation'. Exploration is an algorithm's ability to search broadly through the problem's search space and exploitation is an algorithm's ability to search locally around good solutions that have been found previously. Proper control of global exploration and local exploitation is crucial in heuristic approaches in order to avoid local optimum.

The basic heuristic method is Hill Climbing (HC) or iterative improvement which repeatedly moves to a solution better than the current one until it finds a local optimum (i.e. a solution which is better than all others in its neighborhood). Since only improving moves are accepted, hill climbing tends to get stuck fairly in local optimum, which may be much worse than the global optimum. To overcome this, modern heuristics (or



metaheuristics) are equipped with some way of getting away local optima. The idea is to accept a solution even if it is worse than the current one in order to find better solutions later in the search process. Of course the local optimum is not solved completely yet. The main cause for the local optimal problem in metaheuristics is that algorithms don't make a harmony on exploitation (local improvement) and exploration (global improvement) in search space of solutions.

Generally metaheuristic approaches generate good results. They are suitable when the goal is generating high quality solutions. On the other hand, they are problem-specific and tailor-made nature approaches so that if they are applied to another problem or even another instance of the same problem, lots of effort will be demanded for changing programming and implementation due to match them. Therefore applying of approaches which work at a higher level of generality in different kinds of problem will be justified.

The new generation of heuristic methods is hyperheuristic approaches introduced by (Burke et al., 2003). The development of hyper-heuristics is motivated by the goal of raising level of generality for automatically solving a range of problems.

Hyper-heuristics can be defined to be heuristics which choose between heuristics in order to solve a given optimization problem at a higher level. It means that they don't optimize solutions directly. They work by way of an operator (a low level heuristic). This places a hyper-heuristic at a higher level of abstraction and generality rather than most current studies of metaheuristics. A number of hyper-heuristics have been



developed over the past few years (Cowling, Kendall and Soubeiga, 2000; Ayob and Kendall, 2003; Burke et al., 2007).

Figure 1.1 indicates the general hyper-heuristic framework introduced by (Soubeiga, 2003). Hyper-heuristics can be considered as black box systems, which take the problem instance and several low level heuristics as methods which can produce the result independent of the problem characteristics.

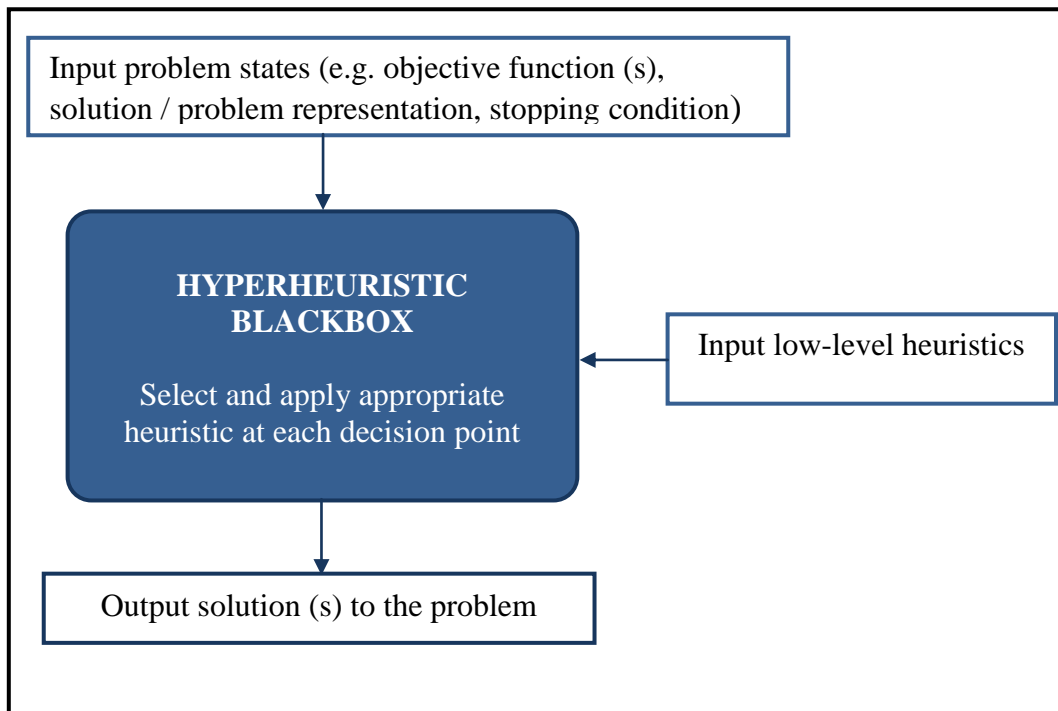


Figure 1.1: General Hyperheuristic Framework

In this concept, hyper-heuristics use only non problem-specific data provided by each low level heuristic in order to select and apply them to candidate solution (Burke et al., 2003).