School Timetabling: Solution Methodologiesand Applications

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ABSTRACT

School timetabling is an important operational problem in many high schools. It is a classical combinatorial optimization problem, proved to be NP-hard. For this reason, extensive research has been carried out on automated high school timetabling in the past 59 years. This research ranges from theoretical investigations and surveysto case studies in specific schools from different countries.Investigation into these case studies demonstrates that school timetabling problems change from one country to another based on different educational systems and philosophies. Design and implementation of algorithms that can deal with this variety of constraints and objectives is a great challenge. Hence, several innovativealgorithmic approachesand techniques including hybrids that promise solutions of high quality have been proposed to solve it. In this article several algorithmic approaches and techniques for this problem is overviewed. In addition to this, thearticle provides an up-to-date survey of the existing literature revealing the current state-of-art approaches and indicatesfuture directions of research in this field for not only those who are working in this field but also for those who might wish to exploit this new methodology.
Keywords: Scheduling, Optimization, Timetabling, Educational Timetabling, School Timetabling.

1. INTRODUCTION

The Timetabling problem (TP) is a resource scheduling problem that can be viewed as a combinatorial optimisation task. It consists of allocating a number of events into a limited number of resources and periods with the aim to satisfy a set of stated objectives to the highest possible extent (Petrovic and Burke, 2004). Timetabling problems arise in various forms of real-world problem solving circumstances including educational timetabling, nurse scheduling, sports timetabling, and transportation timetabling among others. They have represented a challenging and important problem area for researchers across both Operational Research and Artificial Intelligence since the 1960s (Qu *et al*., 2009).

Educational timetabling is one of the mostly studied from a practical viewpoint. It is one of the most important and time-consuming tasks which occur periodically in all academic institutions (Qu *et al*., 2009).Educational timetabling includes university examination, university course and school timetabling (class-teacher scheduling) (Raghavjee and Pillay, 2015).These three classes of educational timetabling problems have been studied as different optimisation problems using different solution methodologies (techniques) to such an extent that methods providing a solution to school timetabling problem may not be effective in solving the course and examination problems (Qu *et al*., 2009; Post et al., 2013).

This article focuses on school timetabling.School timetabling is a classical combinatorial optimization problem proved to be NP-Hard (Even *et al*., 1976;Garey and Johnson, 1979). It consists of assigning a set of lessons to time slots within a time period (typically a week), satisfying a set of constraints of various kinds (Melicio *et al*., 2006, Odeniyi *et al*., 2015).A lesson is the teaching unit. It is characterized by the triple(T^*, C^*, S^*), where $T^*$is a subset of the teachers set, $C^*$is a subset of the classes set and *S**is a subset of the subjects set. Each lesson has a duration measured in time slots (Melicio *et al*., 2003; Odeniyi *et al*., 2015).These constraints are usually classified into two types, hard and soft. Hard constraints must be satisfied in order to provide a feasible solution, whereas, soft constraints which express the preferences and the quality of the timetable can be violated (but must be satisfied as far as possible) (Tassopoulos and Beligiannis, 2012a). The quality of a timetable is measured based on how well the soft constraints have been satisfied. Further discussion on school timetabling can be found in (Pillay, 2014, Odeniyi, 2014).

In the respective literature many models and variants of the School Timetabling Problem (STP) have been presented, which differ due to the educational system of each country, context of the application, the school and the place where it is located. In recent years many papers have been published describing specific methodologies applied to the STP. This article presents an overviewof such methodologiesfor solvingSTP and includes the survey of the existing literatureon these methodologiesas related toschooltimetabling.

The remainder of the paper is structured as follows. The next section presents the solution methodologies. Section 3 provides conclusions drawn from our review indicating future research directions on school timetabling.

2. SOLUTION METHODOLOGIES

Most surveys in school timetabling problems place the several solution methodologiesoriginatingfrom Operational Research, Artificial Intelligence and Computational Intelligence into several categories (Kristiansen and Stidsen, 2013; Pillay, 2014).However, these severalcategories of solution methodologiescan be broadly grouped into two: *exact*and*approximate* and they are discussed in the following subsections.

2.1 Exact Solution Methodologies

Exact methodologyrepresents a classical search method that evokes mathematical procedures. Usually, mathematical formulations are incorporated in order to represent the objective of solving problems and constraint requirements.Exact solution methods can either be of solving the mathematical model using a Mixed Integer Programming (MIP) solver, or by using a number of different exact method approaches based on integer programming such as decomposition and branching techniques (Branch-And-Bound, Column Generation, Branch-And-Price - a combination of branch-and-bound and column generation methods, Branch-And-Cut, Dantzig-Wolf decomposition), dynamic programming, ejection chain and specialized procedureamong others Further information of these methods can be found in (Nemhauserand Wolsey, 1988; Kristiansen, 2014;Dorneles, 2015).

Several papers that discussed the application of these exact methods to school timetabling problemare summarised inTable 1.Exact methodologies are able to find a solution with optimality or quality guaranteed(Dorneles, 2015). However, finding an optimal solution is extremely hard for many optimization problems using exact methodologies due to the problem instance, the properties or given restrictions, hence, near-optimal solutions are usually acceptable rather than finding an optimal solution. Additionally, it may be an issue for exact algorithms to quickly return a solution.particularly when applied on large or complex instances,Furthermore, the mathematical model of these exact methods needs to be carefully developed and treated.Usually, in this case, researchers often sacrifice the optimality to achieve good or feasible solutions in polynomial time, resorting to approximate methodologies (Johnson, 2008; Dorneles, 2015).

Table1: Survey on exact solution methodologies

Technique/Algorithm	Reference and Publication Year	Title/Subject
Integer Programming/Mixed Integer Programming	Lawrie (1969)	An integer linear programming model of aschool timetabling problem
	Tillett (1975)	An operations research approach to the assignment of teachers to courses
	Tripathy (1984)	School timetabling – a case in large binary integer linear programming
	Birbas*et al*.,(1997)	Timetabling for Greek high schools
	Boland*et al*(2008)	New integer linear programming approaches for course timetabling
	Al-Yakooband Sherali(2007)	A mixed-integer programming approach to a class timetabling problem: A case study with gender policies and traffic

		considerations
	Birbas*et al*.,(2009)	School timetabling for quality student and teacher schedules
	Ribic and Konjicija(2010)	A two phase integer linear programming approach to solving the school timetable problem
	Kristiansen*et al*.,(2011)	Elective course planning
	Sorensen and Stidsen(2013)	Integer Programming and Adaptive Large Neighborhood Search for Real-World Instances of High School Timetabling
	Dorneles*et al*.,(2012)	The impact of compactness requirements on the resolution of high school timetabling problem
	PoulsenandBandeira(2013)	A heuristic efficient based on the strategy of division-e-conquest for School Timetabling Problem
	Kristiansen*et al*.,(2015)	Integer Programming for the Generalized (High) School Timetabling Problem
Column Generation	Papoutsis*et al*.,(2003)	A column generation approach for the timetabling problem of Greek high schools
Branch-And-Price	Santos*et al*.,(2008)	Strong bounds with cut and column generation for class-teacher timetabling.
	Santos*et al*.,(2012a)	Strong bounds with cut and column generation for class-teacher timetabling
Branch-And-Bound	PostandRuizenaar(2004)	Cluster schemes in Dutch secondary schools
	de Haan (2004)	Timetabling in dutch secondary schools
	Landman 2005	Creating good-quality timetables for Dutch high schools
Ejection chain and specialised procedure	Kingston (2014)	An algorithm for high school timetabling

2.2 Approximate Solution Methodologies:

An approximate methodology isa search technique which achieve good or feasible (near-optimal) solutions in reasonable running (computational) times but do not guarantee optimality (Johnson, 2008).The following discussion divides approximate methodologies into subsections each considering one of nine categories: classical heuristics, constraint-based, meta-heuristics, hybrid methods,adaptive and knowledge-based, matheuristic, multi-attribute,multi/distributed agent and comparative studymethods.

2.2.1 ClassicalHeuristicMethods

Heuristics strategies are rules of thumbs for discovering good quality solutions in reasonable time, speed up a search process. Although they cannot provide any optimality guarantee, innumerable studies already showed their effectiveness for finding near-optimal solutions in a fast manner. Generally, heuristic methods include *direct heuristics*, *sequential*/*constructive heuristics* and *improvement heuristics*.

Classical heuristic methods employed in school timetabling include *direct heuristics*, *sequential*/*constructive heuristics* and *improvement heuristics*. *Direct heuristics*methodsmimic the manual approach to solving the school timetabling problem (Schaerf, 1999a).*Direct heuristics*approaches usually fill up the complete timetable with one lesson (or one group of lessons) at a time as far as no-conflicts arise. At that point they start making some swapping so as to accommodate other lessons.The favourableness of a period for a lesson is therefore based also on the fact that another lesson of the same teacher to the same class has not been already assigned to a consecutive day

Sequential/*constructive heuristics*methodsbuild a solution from scratch by assigning values to one or more decision variables at a time using backtracking procedures.Thesemethods incorporated the concept of heuristic ordering based on direct heuristic using graph-colouring heuristics, network flow heuristic and Fuzzy based heuristics.*Sequential*/*constructive heuristics* methods are widely studied during the early days of research on school timetabling problems. They are used in sequential (or constructive) solution methods to order the events that are not yet scheduled according to the difficulties of scheduling them into a feasible timeslot (without violating any hard constraints). Events are most often ordered so that those most difficult to schedule are assigned to timeslots first (this course of action being called a direct heuristic based on successive augmentation).

Improvement heuristics methods generally start with a feasible solution and iteratively try to obtain a better solution.Generally, the solutions built by constructive heuristics are improved by the application of a local search procedure which represents the gradual improvement of a current solution(s) starting from initial one(s) until some stopping condition is satisfied (Feo and Resende, 1995;Dorigoand Stützle, 2002). Several papers that discussed the application of classical heuristics to school timetabling problem are summarised in Table 2.

In general, classical heuristic approaches are found to be effective and yet simple approaches for finding a feasible timetabling solution. However, they might not be able to produce a high quality solution with respect to the satisfaction of the soft constraints. To address this situation, hybrid approaches have been studied which incorporate classical heuristics with other techniques.

Furthermore, classical heuristicsshow a great efficiency in small instances of timetabling problems, but are not efficient in large instances.Classical heuristics trade-off concerns such as precision, quality, and accuracy in favour of computational efficiency or effort (space and time efficiency). As classical heuristic approaches can be improved with the addition of a random element, then, random search techniques, such as meta-heuristics were introduced to solve timetabling problems (Melício*et al*., 2005).

Table 2: Survey on classical heuristicmethods

Technique/Algorithm	Reference and Publication Year	Title/Subject
Direct Heuristics	Appleby*et al*., (1961)	Techniques for producing school timetables on computer and their application to other scheduling problems
	Gotlieb (1962)	The construction of class-teacher timetables
	Schmidt andStröhlein (1979)	Timetable construction – an annotated bibliography
	Papoulias (1980)	The assignment-to-days problem in a school time-table, a heuristic approach
	de Gans (1981)	A computer timetabling system for secondary schools in the Netherlands
	Junginger (1986)	Timetabling in Germany- a survey
Sequential/Constructive Heuristics(Graph-Colouring Heuristics)	Lion (1966)	Matrix reduction using the Hungarian method for the generation of school timetables
	Welshand Powell (1967)	The upper bound for the chromatic number of a graph and its application to timetabling problems
	Neufeldand Tartar (1974)	Graph colouring conditions for the existence of solutions to the timetable problem
	de Werra (1985)	An introduction timetabling
	Cooperand Kingston (1993)	The solution of real instances of the timetabling problem
	Asratianand de Werra (2002)	A generalized class–teacher model for some timetabling problems
	Burke*et al*., (2004)	Applications to timetabling
	Bello*et al*., (2008)	An Approach for the Class/Teacher Timetabling Problem using Graph Coloring
Sequential/Constructive Heuristics (Network Flow Heuristics)	de Werra (1971)	Construction of school timetables by flow methods
	Ikeda*et al*., (1995)	School timetabling system: SECTA
	Cooperand Kingston (1995)	A program for constructing high school timetables
	Hertz. and Robert(1998)	Constructing a course schedule by solving a series of assignment type problems
	Ostermann and de Werra (1982)	Some experiments with a timetabling system
Constructive Heuristics	Pimmer and Raidl	A Timeslot-Filling Heuristic Approach to Construct High-School

	(2013)	Timetables
Improvement Heuristics	Aust (1976)	An improvement algorithm for school timetabling

2.2.2 Constraint-Based Methods

Constraint-based methods which include Constraint Programming (CP), Constraint Logic Programing and Constraint Satisfaction techniqueshave been used to a significant extent for solving school timetabling problems. These methodshave their origins in Artificial Intelligence research, and attracted the attention of researchers in timetabling due to the ease and flexibility with which they can be employed for timetabling problems.Generally, in constraint-based methods, a problem is modeled as a set of variables with a finite domain. The method assigns values to variables that fulfill a number of constraints Constraint-based methodsare usually computationally expensive due to the fact that the number of possible assignments increases exponentially with the number of variables. They, on their own, cannot usually provide high quality solutions compared with the state-of-the-art approaches on complex optimisation problems.Different heuristics and techniques are usually integrated with such methods to reduce the time complexity for solving practical problems.

These techniques include: *labelling strategy, Backtracking*(Rossi*et al*., 2006), *Constraint propagation* (Rossi*et al*., 2006), and *Dead-end driven learning* and *restarting* strategies (Frost and Dechter, 1994).The labelling strategy is usually integrated with different problem specific heuristics for variable ordering and is crucial to the success of the method (Qu *et al*., 2009].

In general, constraint-based methods alone can generate feasible solutions efficiently. However, most of these search methods lack the ability to further enhance the quality of the generated solution.Therefore, they are widely applied as a hybridization approach (with other local search methods).(Brailsford*et al*., 1999; Qu *et al*., 2009).Some applications of constraint-based methods include resource allocation, scheduling problems, software configuration and production planning. Constraint-based methods have been used to a significant extent for solving school timetabling problems as summarised in Table 3.

Table 3: Survey on constraint-based methods

Technique/Algorithm	**Reference and Publication Year**	**Title/Subject**
Constraint satisfaction technique	Henzand Würtz(1996)	Using Oz for college timetabling
	Yoshikawa*et al*., (1994)	A constraint-based approach to high school timetabling problems: a case study
	Yoshikawa*et al*., (1996)	A constraint based high school scheduling system
	Meisels*et al*, (1997)	Decomposing and solving timetabling constraint networks
	Marte (1998)	Constraint-based grammar school timetabling – a case study
	Kaneko*et al*., (1999)	Improving a heuristic repair method for large-scale school timetabling problems
	Abbas and Tsang(2001)	Constraint-based timetabling - a case study
	Marte (2002)	Models and algorithms for school timetabling: A constraint programming approach
	Valouxisand Housos (2003)	Constraint programming approach for school timetabling.
	Jacobsen*et al*., (2006)	Timetabling at German Secondary Schools: Tabu Search versus Constraint Programming
	Marte (2007)	Towards constraint-based school timetabling
	Chorbev*et al*., (2008)	Solving the High School Scheduling Problem Modelled with Constraints Satisfaction Using Hybrid Heuristic Algorithms
Logic Programming	Kang and White(1992)	A logic approach to a resolution of constraints in timetabling

2.2.3 Meta-heuristics (Modern/Generalised Heuristics)Methods

Much research in the area of school timetabling has employed meta-heuristic methods with great success. These techniques begin with one or more initial solutions and usually update possible solutions, one or a whole set at a time, and employ search strategies to find optimal solution of a given problem, trying to avoid local optimal in the process (Valouxis and Housos, 2000;MyszkowskiandNorberciak,2003). Essentially, various search strategies such asStochastic Algorithms, Evolutionary Algorithms, Physical Algorithms, Probabilistic Algorithms, Swarm Algorithms, Immune Algorithms and Neural Algorithms are designed to escape from local minima (Brownlee, 2011).

These search strategies are classified into two categories: single-solution and population-based methodsbased algorithms, Single-solution meta-heuristics comprise local-search based algorithms. They deal with a single candidate solution at each iterationto modify and improve They focus on the exploitation (intensification) - searching promising areas in the search space rather than exploration (diversification), which means that they move in one direction without performing a wider scan of the search space.

Population based meta-heuristics employ a population of candidate solutions during the search process often, combining them.At each iteration, one of a number of techniques is applied to the current population to generate the population of the next generation. Therefore, population -based meta-heuristics provide a natural, intrinsic way for the exploration (diversification) of the search space as theyfocused on identifying these promising areas(Blum and Roli, 2003;Chaudhuri and De,2010).Several meta-heuristics have proved to be a valuable tool in solving school timetabling problems as indicated in Table 4 (a-e). The next subsection discusses the various search strategies of meta-heuristics.

Hybrid meta-heuristic methods have also been shown to be particularly effective. An overview of meta-heuristic methods can be found in studies by(Blum and Roli, 2003;Gloverand Kochenberher, 2003, Talbi, 2009).

2.2.3.1 Stochastic Algorithms

Stochastic Algorithms are a class of meta-heuristics that focus on the introduction of randomness into heuristic methods (Brownlee, 2011). This set of algorithms provide various different strategies by which `better' and varied starting points can be generated and issued to a neighbourhood searching technique for refinement, a process that is repeated with potentially improving or unexplored areas to search [80].. Examples are Hill Climbing, Random Search, Iterated Local Search, Guided Local Search, Variable Neighbourhood Search, Greedy Randomized Adaptive Search Procedure, Scatter search, and Tabu Search, among others. A comprehensive discussion on these methods can be found in (Brownlee, 2011;Baghil*et al*., 2012).. Several papers that discussed the application of Stochastic Algorithms to school timetabling problem are summarised in Table 4a.

Table 4a: Survey on meta-heuristics methods - Stochastic Algorithms

Technique/Algorithm	Reference and Publication Year	Title/Subject
Hill Climbing	Wood and Whitaker (1998)	Student Centred School Timetabling
	Wilke and Killer(2010b)	Walk down jump up algorithm—a new hybrid algorithm for timetabling problems
	Fonseca*et al*., (2013)	Late Acceptance-Hill Climbing Applied to the High School Timetabling Problem
Random Search	-	-
Iterated Local Search	Fonseca*et al*., (2012b)	A SA-ILS approach for the high school timetabling problem
	Saviniec and Constantino (2012)	Applying ILS algorithm with a new neighborhood operator to solve a large benchmark of the high school timetabling problem
	Saviniec*et al*., (2013)	Solving the high school timetabling problem to optimality using ILS Algorithms
Guided Local Search	-	-
Large Neighborhood Search	Sorensen*et al*., (2012)	International Timetabling Competition 2011: An Adaptive Large Neighborhood Search algorithm
	Sorensen and Stidsen (2013)	Integer Programming and Adaptive Large Neighborhood Search for Real-World Instances of High School Timetabling
	Kristiansen	Elective course student sectioning at Danish high schools

	andStidsen (2016)	
Very Large Variable Neighborhood Search	Avella*et al.*, (2007)	A computational study of local search algorithms for Italian high school timetabling
Variable Neighborhood Search	Brito*et al.*, (2012)	A SA-VNS approach for the high school timetabling problem
	Fonsecaand Santos (2014)	Variable neighbourhood search based algorithms for high school timetabling
Greedy Randomized Adaptive Search Procedure (GRASP)	Souza*et al.*, (2003)	A GRASP-TABU search algorithm for school timetabling problems
	Souza (2004)	A GRASP-TABU search algorithm for solving school timetabling problems
	Moura and. Scaraficci.(2010)	A GRASP strategy for a more constrained School Timetabling Problem
Scatter Search	-	-
Cyclic transfers	Post*et al.*, (2010)	Cyclic transfers in school timetabling
	Post*et al.*, (2012)	Cyclic transfers in school timetabling
Stochastic local search algorithm	Kheiri *et al.*, (2014)	A stochastic local search algorithm with adaptive acceptance for high-school timetabling
Hybrid local search	Fonseca*et al.*, (2014)	GOAL solver: A hybrid local search based solver for high school timetabling
	Fonseca*et al.*, (2016)	GOAL solver: A hybrid local search based solver for high school timetabling
Tabu Search	Costa (1994)	A tabu search algorithm for computing an operational timetable
	Wright (1996)	School timetabling using heuristic search
	Alvarez-Valdes(1996)	Constructing good solutions for the Spanish school timetabling problem
	Schaerf (1996)	Tabu search techniques for large high school timetabling problems
	Schaerf (1999b)	Local search techniques for large high school timetabling problems
	Colorni*et al.*, (1998)	Meta-heuristics for High-School Timetabling
	Bufe*et al.*, (2001)	Automated Solution of a Highly Constrained School Timetabling Problem - Preliminary Results
	Alvarez-Valdes(2002)	A tabu search algorithm for assigning teachers to courses
	Lohnertz (2002)	A timetabling system for the German gymnasium
	Willemen (2002)	School timetabling construction: algorithms and complexity
	Santos*et al.*, (2004)	An Efficient Tabu Search Heuristic for the School Timetabling Problem
	Santos*et al.*, (2005)	A Tabu search heuristic with efficient diversification strategies for the class/teacher timetabling problem
	Jacobsen*et al.*, (2006)	Timetabling at German secondary schools: tabu search versus constraint programming
	Ohtsubo*et al.*, (2006)	Approach to the timetabling problems for junior high schools
	Desef*et al.*, (2006)	A Tabu Search Algorithm for Solving the Timetabling-Problem for German Primary Schools
	de Haan*et al.*, (2007a)	A case study for timetabling in Dutch high schools.
	Liu*et al.*, (2009)	A simulated annealing algorithm with a new neighborhood structure for the timetabling problem
	Minh*et al.*, (2010)	Using Tabu Search for Solving a High School Timetabling Problem

2.2.3.2 Physical Algorithms

Physical algorithms are a class of algorithms inspired by a physical processfor their computational strategy. In this vein, they could just as easily be referred to as nature inspired algorithms. The inspiring physical systems range from astronomy, electromagnetism, social sciences, metallurgy, music, the interplay between culture and evolution, and complex dynamic systems such as avalanches. They are generally stochastic optimization algorithms with mixtures of local (neighbourhood-based) and global search techniques (Brownlee, 2011). Examples are Simulated Annealing and its extensions, Harmony Search, Cultural Algorithm and Memmetic Algorithm among others. A comprehensive discussion on these methods can be found in (Brownlee, 2011). Several papers that discussed the application of Physical Algorithms to school timetabling problem are summarised in Table 4b.

Table 4b: Survey on meta-heuristics methods - Physical Algorithms

Technique/Algorithm	**Reference and Publication Year**	**Title/Subject**
Threshold Accepting	Abboud*et al*., (1998)	School scheduling using threshold accepting
Great Deluge	Wilke and Killer(2010b)	Walk down jump up algorithm—a new hybrid algorithm for timetabling problems
Harmony Search	-	-
Tiling Algorithm	Kingston (2004)	A tiling algorithm for high school timetabling
	Kingston (2006)	The KTS high school timetabling systems
	Kingston (2008)	Resource assignment in high school timetabling
Walk Down Jump Up Algorithm	Wilkeand Killer(2010b)	Walk down jump up algorithm—a new hybrid algorithm for timetabling Problems
Simulated Annealing	Abramson (1991)	Constructing school timetables using simulated annealing
	Abramson and Dang (1993)	School Timetable: A Case Study in Simulated Annealing
	Abramson*et al*., (1996)	Simulated annealing cooling schedules for the school timetabling problem
	Colorni*et al*., (1998)	Meta-heuristics for High-School Timetabling
	Melicio*et al*., (2006)	THOR: A tool for school timetabling
	Avella *et al*., (2007)	A computational study of local search algorithms for Italian high school timetabling
	Yongkai*et al*., (2009)	A simulated annealing algorithm with a new neighbourhood structure for the timetabling problem
	Liu *et al*., (2009)	A Simulated Annealing Approach with a new Neighbourhood Structure for the Timetabling Problem
	Zhang*et al*., (2010)	A simulated annealing with a new neighborhood structure based algorithm for high school timetabling problems
	Santos*et al*., (2012b)	A SA-ILS approach for the high school timetabling problem.
	Fonseca*et al*., (2012a)	A simulated annealing based approach to the high school timetabling problem
	Fonseca*et al*., (2012b)	A SA-ILS approach for the high school timetabling problem.
	Brito*et al*., (2012)	A SA-VNS approach for the high school timetabling problem
Hybrid local search	Fonseca*et al*., (2014)	GOAL solver: A hybrid local search based solver for high school timetabling
	Odeniyi *et al*., (2015)	Development of a modified simulated annealing to school timetabling problem
Cultural Algorithm	-	-
Memetic Algorithm	Wilke*et al*., (2002)	A Hybrid Genetic Algorithm for School Timetabling
	FonsecaandSantos (2013)	Memetic Algorithms for the High School Timetabling Problem

2.2.3.3 Evolutionary Algorithms

Evolutionary Algorithms (EAs) are algorithms inspired from the natural selection, mutation and recombination of the biological mechanism (Yuce*et al*., 2013). EAs work with a random population of solutions, and efficiently exploit historical information to speculate on new search areas with improved performance. In EAs, the main strategy is to find the optimal points by utilizing the stochastic search operators such as natural selection, mutation and recombination to the population.. When applied to optimization problems, the EA has the advantage of performing a global search.

There are so many types of EAs available with Genetic Algorithm being the most common. Each one of the methods models the evolution of a population of individuals at a different scale and applies selection and reproduction operators to find an individual that is fit with regard of the fitness function (Brownlee, 2011).. Other EA methods include Genetic Programming, Evolutionary Strategies, Evolutionary Programming, Differential Evolution, among others. A comprehensive discussion of these methods can be found in (Brownlee, 2011; Ab-Wahab*et al*., 2015).Few papers that discussed the application of Evolutionary Algorithms to school timetabling problems are summarised in Table 4c.

Table 4c: Survey on meta-heuristics methods - Evolutionary Algorithms

Technique/Algorithm	Reference and Publication Year	Title/Subject
Evolutionary Algorithms/ Genetic Algorithms	Colorni*et al*., (1990)	Genetic algorithms: a new approach to the timetable problem
	Abramson and Abela(1991)	A parallel genetic algorithm for solving the school timetabling problem
	Monfroglio (1996)	Timetabling through constrained heuristic search and genetic algorithms
	Drexland Salewski(1997)	Distribution requirements and compactness constraints in school timetabling
	Caldeira and Rosa(1997)	School Timetabling using Genetic Search
	Fernandes*et al*., (1999a)	High school weekly timetabling by evolutionary algorithms.
	Fernandes*et al*., (1999b)	Evolutionary algorithm for school timetabling
	Bufe *et al*., (2001)	Automated solution of highly constrained school timetabling problem
	Di Stephano and Tettamanzi (2001)	An evolutionary algorithm for solving the school timetabling problem
	Filho& Lorena, (2001	A Constructive Evolutionary Approach to School Timetabling
	Győri*et al*., (2001)	A New Approach for Genetic Algorithms Based Timetabling in Schools
	Carrascoand Pato(2001)	A Multi-objective Genetic Algorithm for the Class/Teacher Timetabling Problem
	Lima*et al*., (2001)	Class scheduling through genetic algorithms
	Wilke *et al*., (2002)	A Hybrid Genetic Algorithm for School Timetabling
	Bedoya and Santos(2003)	A non-standard genetic algorithm approach to solve constrained school timetabling problems
	Ciscon*et al*., (2006)	The school timetabling problem: a focus on elimination of open periods and isolated classes
	Nurmi and Kyngas(2007)	A framework for school timetabling problem
	Yigit (2007)	Constraint-Based School Timetabling Using Hybrid Genetic Algorithms
	Zuters (2007)	Neural networks to enrich fitness function in a GA-based school timetabling model
	Beligiannis*et al*., (2008)	Applying evolutionary computation to the school timetabling problem: The Greek case
	Mohammadi	Cooperative co-evolution for school timetabling problem

	andLucas (2008)	
	Nurmiand Kyngas(2008)	A Conversion Scheme for Turning a Curriculum Based Timetabling Problem into a School Timetabling Problem
	Raghavjee and Pillay(2008)	An application of genetic algorithms to the school timetabling problem
	Cedeira-Pena*et al*., (2008)	New approaches for the school timetabling problem
	Beligiannis*et al*., (2009)	A genetic algorithm approach to school timetabling
	Moschopoulos*et al*., (2009)	A User-Friendly Evolutionary Tool for High-School Timetabling
	Raghavjee and Pillay(2009)	Evolving solutions to the school timetabling problem
	Srndic*et al*., (2009)	The application of a parallel genetic algorithm to timetabling of elementary school classes: a coarse grained approach
	Raghavjee and Pillay(2010a)	An informed genetic algorithm for the high school timetabling problem
	Raghavjee and Pillay(2010b)	Using genetic algorithms to solve the South African school timetabling problem
	Raghavjee and Pillay, (2012)	A comparison of genetic algorithms and genetic programming in solving the school timetabling problem
	Domrös and Homberger (2012)	An evolutionary algorithm for high school timetabling
	Raghavjee (2013)	A Study of Genetic Algorithms for Solving the School Timetabling Problem
	Raghavjee and Pillay(2013)	A study of genetic algorithms to solve the school timetabling problem
	Shambour*et al*., (2013)	A two stage approach for high school timetabling
	Sutar and Bichkar(2017)	Parallel Genetic Algorithm for High School Timetabling

2.2.3.4 Swarm Intelligence (SI) algorithms

Swarm Intelligence (SI) algorithms belong to the family of population based stochastic techniques which are based on some sort of agents interacting locally with one another and with their environment.SI mimics the collective exploration strategy of the swarms in the nature on optimization problems. SI paradigm consists of two dominant sub-fields (i) Ant Colony Optimisation (Ant Algorithms) that investigates probabilistic algorithms inspired by the stigmergy and foraging behaviour of ants, and (ii) Particle Swarm Optimisation that investigates probabilistic algorithms inspired by the flocking, schooling and herding. Like evolutionary computation, swarm intelligence `algorithms' or `strategies' are considered adaptive strategies and are typically applied to search and optimization domains (Brownlee 2011).
Other algorithms and classes of algorithm from the field of SI includeArtificial Fish Swarm Algorithm,Honey-bee Mating Optimization (Bee Algorithms), Fiery Algorithm, Wasp Swarm Algorithm, Bacteria Algorithms: and others such as Glowworm Swarm Optimization Algorithm, Cuckoo Search Algorithm, Bat algorithm, Grey Wolf Optimiser and Cat SwarmOptimization among others. A comprehensive discussion on these Swarm Intelligence (SI) algorithms can be found in (Brownlee 2011;Ab-Wahab *et al*., 2015).
Few papers that discussed the application of Swarm Intelligence Algorithms to school timetabling problem are summarised in Table 4d.

2.2.3.5 Neural Algorithms

Neural Algorithms are inspired by the plasticity and learning qualities of the human nervous system.Neural models are generally designed as models for addressingmathematical, computational, and engineering problems. As such, there is a lot of interdisciplinary research in mathematics, neurobiology and computer science (Brownlee 2011).

Table 4d: Survey on meta-heuristics methods - Swarm Intelligence Algorithms

Technique/Algorithm	Reference and Publication Year	Title/Subject
Particle Swarm Optimisation Algorithm	Tassopoulosand Beligiannis (2012a)	Solving Effectively the School Timetabling Problem Using Particle Swarm Optimization
	Tassopoulosand Beligiannis (2012b)	A Hybrid Particle Swarm Optimization Based Algorithm for High School Timetabling Problems
	Tassopoulosand Beligiannis (2012c)	Using particle swarm optimization to solve effectively the school timetabling problem
	Katsaragakis*et al*., (2015)	A comparative study of modern heuristics on the school timetabling problem
Artificial Fish Swarm Algorithm	Katsaragakis*et al*., (2015)	A comparative study of modern heuristics on the school timetabling problem
Honey-bee Mating Optimization (Bee Algorithms)	Lara*et al*., (2008)	Solving a school timetabling problem using a bee algorithm
Ant Algorithms (Ant Colony Optimization)	-	-
Fiery Algorithm	-	-
Wasp Swarm Algorithm	-	-
Bacteria Algorithms	-	-
Glowworm Swarm Optimization	-	-
Cuckoo Search Algorithm	-	-
Bat algorithm	-	-
Grey Wolf Optimiser	-	-
Cat Swarm Optimization	-	-

Due to the collective computation properties of some neural models, the area of artificial neural networks have contributed this neural algorithms based approach, although possibly not so relevant as the former ones, to the combinatorial optimization problem solving with the Hopfield neural networks algorithms (Hopfield and Tank, 1985; Licas and Stafylopatis, 1996; Smith*et al*., 1998, 2003); the Boltzmann machine algorithms (Aarts and Korst, 1989) and the self-organizing map algorithms (Kohonen, 1998).

Generally, Hsiao-Lan (1994) reported that different researchers have used different neural network models to deal with timetabling or scheduling problems using Feedback neural networks and Potts neural networks, and have been extended by Gislen*et al*., (1992) to deal with larger timetabling problems. A comprehensive discussion on neural algorithms can be found in(Brownlee, 2011). Few papers that discussed the application of Neural Algorithms to school timetabling problem are summarised in Table 4e.

Table 4e: Survey on meta-heuristics methods - Neural Algorithms

Technique/Algorithm	Reference and Publication Year	Title/Subject
Hopfield Neural Networks	Smith*et al*., (2003)	Hopfield neural networks for timetabling: Formulations, methods, and comparative results
	Carrasscoand Pato(2004)	A comparison of discrete and continuous neural network approaches to solve the class/teacher timetabling problem
Boltzmann Machine	-	-
Self-Organizing Map	-	-

2.2.3.6 Probabilistic Algorithms

Probabilistic Algorithms are those algorithms that model a problem and search a problem space or estimate distributions in search domains using a probabilistic model of candidate solutions, typically in a component-wise or step-wise manner

using a domain specific construction method to ensure validity. The main feature of probabilistic algorithms is the explicit (rather than implicit) use of the tools of probability in problem solving (Brownlee, 2011).
They generally involve iterations that alternate between creating candidate solutions in the problem space from a probabilistic model, and reducing a collection of generated candidate solutions into a probabilistic model. Typically, the probabilistic model provides the probabilistic expectation of a component or component configuration comprising part of an optimal solution. This estimation is typically based on the observed frequency of use of the component in better than average candidate solutions (Brownlee, 2011).
Examples are Population-Based Incremental Learning Algorithm, Univariate Marginal Distribution Algorithm, Bayesian Optimisation Algorithm, among others (Brownlee, 2011). A comprehensive discussion on Probabilistic Optimisation Algorithms can be found in (Brownlee, 2011;Pelikan*et al*., 2002;Pelikan*et al*., 2006; Larranaga and Lozano, 2002; Lozano*et al*., 2006). No paper to the best of the authors has discussed the application of Probabilistic Algorithms to school timetabling problem.

2.2.3.7 Immune Algorithms

Immune Algorithms are a class of algorithms inspired by the adaptive immune system of vertebrates.They belong to the Artificial Immune Systems field of study concerned with computational methods inspired by the process and mechanisms of the biological immune system (Brownlee, 2011). The early works in the field were inspired by exotic theoretical models (immune network theory) and were applied to machine learning, control and optimization problems. The approaches were reminiscent of paradigms such as Artificial Neural Networks, Genetic Algorithms, Reinforcement Learning, and Learning Classifier Systems. The most formative works in giving the field an identity were those that proposed the immune system as an analogy for information protection systems in the field of computer security (Brownlee, 2011).
Examples include Clonal Selection Algorithms (such as,the Multi-Objective Immune System Algorithm,and the Optimization Immune Algorithm), Immune Network Algorithms, and Negative Selection Algorithms among others. A comprehensive discussion on these Swarm Intelligence (SI) algorithms can be found in (Brownlee, 2011). No paper to the best of the authors has discussed the application of Probabilistic Algorithms to school timetabling problem.

2.2.4 Hybrid Methods

As extensions of meta-heuristic algorithms, hybrid algorithms have been developed to improve the performance and exploit simultaneously the advantages of original meta-heuristic algorithms. The inspiration for hybridisation of different algorithms is to accomplish the interrelated behaviour of different optimisation strategies (Baghil *et al*., 2012). The main aim of developing hybrid algorithms is to produce advanced search methods that are greater than the sum of their individual parts and to provide an adequate balance between the exploration (diversification) and exploitation (intensification) mechanisms. The exploration mechanism is related to the ability of algorithm to perform efficient search in solution space of the optimization problem, while the exploitation mechanism is related to the ability of finding better solutions in the vicinity of the current solutions (Blum and Roli, 2003;Jalili andHosseinzadeh, 2015).

Such hybrids have been proven to be very effective in the optimisation literature, and particularly in school timetabling. Experiments have shown the advantages of such a hybrid method over the “pure” heuristic methods (Burke*et al*., 1996;Burke*et al*., 1998;Socha*et al*., 2002;Alkan and Ozcan, 2003;Gallardo*et al*., 2007;Oyeleye*et al*., 2014;Alia*et al*., 2016)among others. The combination of different meta-heuristic can be done in several ways. Details can be found in (Talbi, 2002; Müller, 2005;Puchinger and Raidl, 2005;Blum*et al*., 2005;Chorbev *et al*., 2008, Baghil *et al*., 2012;Fong*et al*., 2015; Alia*et al*., 2016). While hybridisation has its advantages, it also comes with a potential cost. First, there is need to balance the component algorithms in terms of exploration and exploitation (Ghosh*et al*., 2012; Odeniyi, 2014). Second, with more algorithms under the hood, the optimisation engine may require more computational resources in the worst case. It is important thus, keeping the hybrid algorithm simple can help to limit the number of function evaluations needed to solve a problem (Becerra and Coello, 2006; Ali and Awad,2014).

Hence, a final balance is required so that an algorithm can achieve good performance. However, how to achieve such balance is still an open problem. In addition, such balance may depend on many factors such as the working mechanism of an algorithm, its setting of parameters, tuning and control of these parameters and even the problem to be considered (Yang, 2014). In other words, the degree of exploitation should be monotonically decreasing and the degree of exploration should be monotonically increasing during the search run (Saini, 2017). Such observations motivated the development of hyper-heuristic based approaches. Several papers that discussed the application of hybrid approaches to school timetabling problem are summarised in Table 5

Table 5: Survey on hybrid methods

Technique/Algorithm	Reference and Publication Year	Title/Subject
(i) Arc consistency (ii) Hill Climbing	Yoshikawa*et al*., (1994)	A constraint-based approach to high school timetabling problems: a case study
(i) Arc consistency (ii) Hill Climbing	Yoshikawa*et al*., (1996)	A constraint based high school scheduling system
(i) Tabu Search (ii) Randomize Non Ascendant	Schaerf (1996)	Tabu search techniques for large high school timetabling problems
(i) Tabu Search (ii) Floyd-Warshall Algorithm	Alvarez-Valdes*et al*., (1996)	Constructing good solutions for the Spanish school timetabling problem
(i) Genetic algorithms (ii) Constrained heuristic search	Monfroglio (1996)	Timetabling through constrained heuristic search and genetic algorithms
(i) Greedy RandomizedAlgorithms (ii) Genetic algorithms	Drexl and Salewski(1997)	Distribution requirements and compactness constraints in school timetabling
(i) Tabu Search (ii) Randomize Non Ascendant	Schaerf (1999b)	Local search methods for high school timetabling problems
(i) Tabu Search (ii) Graph Vertex Coloring Algorithm	Lohnertz (2002)	A timetabling system for the German gymnasium
(i) Tree Search Algorithm (ii) Tabu Search	Willemen (2002)	School timetabling construction: algorithms and complexity
(i) GRASP (ii Tabu Search	Souza*et al*., (2003)	A GRASP-tabu search algorithm for school timetabling problems
(i) GRASP (ii)Tabu Search	Souza (2004)	A GRASP-tabu search algorithm for solving school timetabling problems
(i) Constraint technology (ii) Heuristics (iii)Local search with a Tabu List	Kwan*et al*., (2003)	An automated school timetabling system using hybrid intelligent techniques
(i) Tiling algorithm (ii) Hill Climbing (iii An Alternating Path Algorithm	Kingston (2004)	A tiling algorithm for high school timetabling
(i) Tiling algorithm (ii) Hill Climbing (iii An Alternating Path Algorithm	Kingston (2006)	The KTS high school timetabling systems
(i) Beam search (ii Branch and Bound Algorithm	de Haan (2004)	Timetabling in dutch secondary schools
(i) Clustering Algorithm (ii) Branch and bound algorithm	Postand Ruizenaar(2004)	Cluster schemes in dutch secondary schools
(i) Beam Search (ii) Branch and Bound Algorithm, (iii) Shifting algorithm (iv) Re-Coloring Algorithm	Landman (2005)	Creating good-quality timetables for Dutch high schools
(i) Clustering algorithm (ii) Tabu Search	de Haan*et al*., (2007a)	A case study for timetabling in Dutch high schools
(i) Branch and Bound Algorithm (ii) Dynamic Priority Rule (iii) First-Fit Heuristic (iv) Tabu Search	de Haan*et al*., (2007b)	A four-phase approach to a timetabling problem for secondary schools
(i) Very Large Variable Neighborhood Search (ii) Simulated Annealing	Avella*et al*., (2007)	A computational study of local search algorithms for Italian high school timetabling
(i) Genetic Algorithms (ii) Neural networks	Zuters (2007)	Neural networks to enrich fitness function in a GA-based school timetabling model
(i) Constraint Programming	Chorbev*et al*., (2007)	Hybrid Heuristics for Solving the Constraints

(ii) Simulated Annealing (iii) Tabu Search (iv) Guided Search		Modelled High School Scheduling Problem.
(i) Constraint Programming (ii) Simulated Annealing (iii) Tabu Search (iv) Guided Search	Chorbev*et al*., (2008)	Solving the High School Scheduling Problem Modelled with Constraints Satisfaction Using Hybrid Heuristic Algorithms
(i) Random Ascendant Method (ii) Genetic algorithms	Cedeira-Pena*et al*., (2008)	New approaches for the school timetabling problem
(i) Simulated Annealing (ii) Tabu Search	Liu*et al*., (2009)	A simulated annealing algorithm with a new neighborhood structure for the timetabling problem
(i) Walk Down Jump Up Algorithm (ii) Hill Climbing (iii) A Jump Operator (iv) Great Deluge	Wilke and Killer(2010b)	Walk down jump up algorithm—a new hybrid algorithm for timetabling problems
(i) Simulated Annealing (ii) Iterative Local Search	Fonseca*et al*., (2012b)	A SA-ILS approach for the High School Timetabling Problem
(i) Genetic Algorithms (ii) Genetic Programming	Raghavjee and Pillay(2012)	A comparison of genetic algorithms and genetic programming in solving the school timetabling problem
(i) Integer Programming (ii) Adaptive Large Neighborhood Search	SorensenandStidsen(2013)	Integer Programming and Adaptive Large Neighborhood Search for Real-World Instances of High School Timetabling
(i) Tabu Search (ii) Genetic Algorithm	Sutar and Bichkar(2017)	High school timetabling using tabu search and partial feasibility preserving genetic algorithm

2.2.5 Adaptive and Knowledge-based Methods

Meta-heuristics though effective are with some limitations. Meta-heuristicsmethods are dependent on certain parameters tuning. For example, simulated annealing depends on a cooling schedule; tabu search requires (among other parameters) an appropriate length of tabu list, genetic algorithms, for example, might need to tune the length of a chromosome. The performance of these meta-heuristics methods varies from one instance to another which might depend on the setup of these parameters, the neighbourhood structure (the manner in which the neighbourhood is defined), the search algorithm itself and the way of embedding domain knowledge (that is the hard coding of hard and soft constraints) (Qu *et al*., 2009).

Thus, meta-heuristic implementations often have a *tailor-made* aspect to their nature. Many meta-heuristic approaches work well on certain problem instances but often are not readily applicable and are expensive to adapt to new problems (Abdullah, 2006). Such limitations motivated the development of new methods – adaptive and knowledge-based methods aimed at operating at a higher level of generality.In adaptive and knowledge-based methods information (experience) collected during the problem solving is used to guide (drive) the search..The goal is to deal automatically with different problems in a dynamic way so that extra effort is not needed to fine-tune the approach. These techniques include hyper-heuristics, case-based reasoning and expert systemsamong others and they are discussed in the following subsections

2.2.5.1 Hyper-heuristics

Hyper-heuristics asan example of adaptive system is a search method in which several heuristics are combined and adaptedto provide a more generalized solution for a problem domain.They are some sort of hybridization of multiple heuristics being used as solution methods (Burke*et al*., 2003a).The term hyper-heuristic is to describe heuristics to choose heuristics in the context of combinatorial optimization as wellas a search method or learning mechanism for selecting or generating heuristics to solve computational search problems (Misir, 2012;Burke et al., 2013).

The distinguishing feature of hyper-heuristics is that they operate on a search space of heuristics (or heuristic components) rather than directly on the search space of solutions to the underlying problem that is being addressed. The heuristic space is usually comprised of combinations of low-level heuristics which can be constructive or perturbative (improvement)(Burke*et al*., 2003b).Construction heuristics are used to construct a solution to a combinatorial optimization problem, while perturbative heuristics are used to improve an initial potential solution which is usually created using a construction heuristic

Various strategies and methodologies have been employed as the high level selection methods in a hyper-heuristic framework to choose appropriate low level heuristics. These low level heuristics might be either construction or improvement heuristics. Such methods are laying the foundations of methodologies to automatically design and adapt timetabling heuristics. Further details can be found in (Burke*et al*., 2003b; Burke and Kendall, 2005; Misir, 2012; Burke*et al*., 2013;Raghavjee and Pillay, 2015).There has not been much research into the use of hyper-heuristics for solving the school timetabling problem as indicated in Table 6.

2.2.5.2 Case-Based Reasoning

Case-Based Reasoning (CBR) is a knowledge-based technique that solves new problemsbased on knowledge and experiences from old problems that have been previously collectedin the form of cases and stored in a case base (source cases) (Leake, 1996). In a CBR system, a case base store a set of previously solved problems with their good solutions or problem solving strategies (called source cases). A similarity measure, usually defined as a formula, is used to assess the similarities between the target case and source cases. The good solutions or problem solving strategies of the most similar source case are reused to tackle the target case.
The overall idea of CBR ismotivated by the human process of learning from previous experience and using that experience to solve new problems, and hence that by retrieving the most similar source case(s), CBR is capable of solving problems based onprevious good solutions, avoiding solving problems from scratch and saving a lot of effort. Further details can be found in (Kolodner, 1993; Burke,*et al*., 2006), while an overview of CBR on educational timetabling can be found in(Petrovic and Burke, 2004).CBR has been employed with some success on some scheduling problems (MacCarthyandJou, 1996). However, no paper to the best of the authors has discussed the application of CBR to school timetabling problem.

2.2.5.3 Expert System

Expert system is a knowledge-based techniques use a rule-based system or fuzzy-based system to solve problems by simulating knowledge from an experienced human expert modeled as a set of rules. Rules are stored in a knowledge base and are inferred by the inference engine. Solution techniques based on expert systems are given in (Miesel *et al*., 1991;Solotorevsky *et al*., 1994). In (Solotorevsky *et al*., 1994) a rule-based language, called RAPS, is defined for specifying general resource allocation problems. Further details can be found in (Solotorevsky *et al*., 1994). Few papers that discussed the application of expert system to school timetabling problem are summarised in Table 6.

Table 6: Survey on adaptive and knowledge-based methods

Technique/Algorithm	Reference and Publication Year	Title/Subject
Hyper-heuristics	Ross*et al*., (2004)	Hyper-heuristics applied to class and exam timetabling problems
	Ross and Marıin (2005)	Constructive hyper-heuristics in class timetabling
	Pillay (2010)	A study into the use of Hyper-Heuristics to solve the school timetabling
	Pillay (2011a)	A hyper-heuristic approach to solving school timetabling problems
	Pillay (2011b)	Evolving Heuristics for the School Timetabling Problem
	Pillay (2012)	Hyper-heuristics for educational timetabling
	Pillay (2013)	A Comparative Study of Hyper-Heuristics for Solving the School Timetabling Problem
	Pillay and Raghavjee(2015)	A genetic algorithm selection perturbative hyper-heuristic for solving the school timetabling problem
	Ahmed *et al*., (2015)	Solving high school timetabling problems worldwide using selection hyper-heuristics
Case - Based Reasoning	-	-
Expert System	Kong and Kwok (1999)	A conceptual model of knowledge-based timetabling system

2.2.6 MatheuristicsMethods

Matheuristics(by the contraction of Mathematical Optimization and Meta-heuristics) is a result of the hybridization ofexact methods and meta-heuristics to exploit simultaneously the advantages of these methods (Dumitrescu andStützle, 2003; Puchinger and Raidl, 2005; Raidl, 2006;Jourdan*et al*., 2009).A matheuristic is a type of hyper-heuristic where meta-heuristics and mathematical programming techniques are embedded in terms of a master-slave structure. That is, either (i) themeta-heuristic acts as master at a higher level and controls the exact approach or (ii) the exact method acts as the master and controls the meta-heuristic(Caserta and Voss, 2010). The exact methods such as Mixed Integer Programing (MIP) solvers or customized MIP algorithms, such as decomposition, are used in a heuristic context, either as primary solvers or as sub procedures (Avella *et al*., 2007;Maniezzo*et al*., 2009a, Maniezzo*et al*., 2009b).

A class of matheuristics methods that had obtained significant success are the fix-and-optimize approach, column generation,cut and column generation. Few papers that discussed the application of matheuristics to school timetabling problem are summarised in Table 7.

Table 7: Survey on matheuristics methods

Technique/Algorithm	Reference and Publication Year	Title/Subject
(i) Simulated Annealing (ii) Fix-and-Optimize approach (Very Large Scale Neighborhood Search and MIP Solver)	Avella *et al*., (2007)	A computational study of local search algorithms for Italian high school timetabling
(i) Integer Programming (ii) Heuristic based on the division-and-conquest strategy,	Poulsen and Bandeira (2013)	A heuristic efficient based on the strategy of division-e-conquest for School Timetabling Problem
(i) Mixed Integer LinearProgramming, (ii) Fix-and-Optimize Heuristic (iii) Variable Neighborhood Descent Method	Dorneles*et al*., (2014)	A fix-and optimize heuristic for the high school timetabling problem
(i) Greedy Algorithm (ii) Generic IP Solver	Sorensenand Stidsen (2014)	Hybridizing integer programming and meta-heuristics for solving high school timetabling.
(i) Fix-and-Optimize (ii) Column Generation (iii) Brach-and-Price Approaches	Dorneles (2015)	A Matheuristic Approach for solving the High School Timetabling Problem
(i) Fix-and-Optimize (ii) Local Branching	Dorneles*et al*., (2016)	Solving large high school timetabling problems in Brazil by using fix-and-optimize and local branching
(i) Mixed Integer Linear Programming (ii) Column Generation	Dorneles*et al*., (2017)	A column generation approach to the high school timetabling modeled as a multicommodity flow problem

2.2.7 Multi-attribute (Multi-criteria/Multi-objective)Methods

In the majority of approaches on timetabling, weighted costs of violations of different constraints are summed and used to indicate the quality of the solutions thereby considering the problem a single/mono-objective problem. However, in real world circumstances, many criteria arise in solving the problem, the simple sum of costs on different constraints cannot always take care of the situation in such cases. Multi-attribute techniques have been studied in timetabling with the aim of handling different constraints easily by considering a vector of constraints instead of a single weighted sum (Abounacer*et al*., 2010). Multi-attribute methods offer a more flexible way of dealing with problems involving more than one objective function to be simultaneously optimized (Ayob *et al*., 2007). The method considers several criteria for making decisions and is able to handle these simultaneously. A variety of techniques have been addressed in the literature to deal with multi-objective optimization that can be classified into three approaches: a priori, a posteriori, and progressive (Amine, 2019).

An a priori approach consists of a transformation of the mathematical multi-objective model into a mono-objective one. Many methods have been introduced from this perspective, namely, goal programming, aggregation or scalarisation, and lexicographical, which return typically one (Pareto) optimal solution of the original model. An a posteriori approach consists of a construction of the Pareto set. Yet, such a construction is usually difficult and computationally consuming. Thus, approximation algorithms are plausibly suggested in this case. They consist in constructing a subset of the Pareto set, or otherwise a set of efficiently non-dominated (or near-Pareto optimal) solutions, that is, feasible solutions that are not dominated by any solution that can be alternatively computed in reasonable computational cost. The construction of the actual or an approximatingPareto set is sometimes referred to as Pareto optimization (Amine, 2019).

As to progressive approach, also called interactive approach, it is a hybridization of the two aforementioned approacheswhere the decision-maker provides a kind of guidance tothe algorithm execution. It consists actually of an a prioriapproach that involves an a posteriori partial result learningand preference defining as long as the algorithm progresses (Amine, 2019).More details about progressive optimization can be found in(KorhonenandWang, 2005, SorensenandSpringael, 2014). Further detail onmulti-attributemethods can be found in (Petrovic and Burke, 2004). Meta-heuristics have been widely adapted to cope with multi-objective combinatorial problems. However, the only paper to the best of the authors that discussed the application of multi-attribute methods to school timetabling problem are summarised in Table 8.

Table 8: Survey on multi-attribute methods

Technique/Algorithm	Reference and Publication Year	Title/Subject
Multi-objective Algorithm	Carrasscoand Pato (2001)	A Multi-objective Genetic Algorithm for the Class/Teacher Timetabling Problem

2.2.8 Multi/Distributed Agent and Decomposition Methods

In multi/distributed agent methods, the whole problem will be decomposed into several sub-problems and distributed between independent subroutines (*agents*). Each agent will use a technique, for example constraint logic approach for the partial optimization of its own sub-problem.The partially optimized sub-problems will be sent to a special central agent (*broker*), which will optimize the remaining parts. The final solution will be aggregated from the parts, solved by the agents and the broker. Further detail on multi/distributed agent can be found in (Wangmaeteekul, 2011).

In decomposition methods, the larger problem is decomposed into a series of smaller sub-problems. The sub-problems are ordered by “how difficult” each event in the sub-problem is to be scheduled.This difficulty measure can be provided by graph - based coloring heuristics. In addition “look ahead” techniques are used where the current sub-problem is not fixed in place until the next one had been dealt with. The motivation here was to try and avoid situations where scheduling decisions that were taken in an earlier sub-problem would lead to infeasibilities in later sub-problems.

Few papers that discussed the application of multi/distributed agent and decomposition methods to school timetabling problem are summarised in Table 9.

Table 9: Survey on multi/distributed agent and decomposition methods

Technique/Algorithm	Reference and Publication Year	Title/Subject
Decomposition	Slechta (2005)	Decomposition and parallelization of multi-resource timetabling problem
	Valouxis*et al*., (2012)	Decomposing the High School Timetable Problem.
	Sørensen (2013)	Decomposing the generalized high school timetabling problem
	Shambour*et al*., (2013)	A two stage approach for high school timetabling
	Sorensenand Dahms (2014)	A Two-Stage Decomposition of High School Timetabling applied to cases in Denmark
Hierarchical approach	Kingston (2007)	Hierarchical timetable construction
KHE general problem solver	Kingston (2010)	Solving the general high school timetabling problem

2.2.9 Comparative Study Method

One of the methods proposed for the solution of timetabling problems is by comparing several techniques in order to demonstrate their efficiency and performance. Few papers that discussed the application of comparative study method to school timetabling problem are summarised in Table 10.

Table 10:Survey on comparative study method

Technique/Algorithm	Reference and Publication Year	Title/Subject
(i) Simulated Annealing, (ii) Tabu Search with Local Search (iii) Genetic Algorithms	Colorni *et al*., (1998)	Metaheuristics for high school timetabling
(i) Hopfield Neural Network (ii) Greedy Search (iii) Simulated Annealing (iv) Tabu Search.	Smith *et al*., (2003)	Hopfield neural networks for timetabling
(i) Tabu Search (ii) Simulated Annealing (iii) Genetic Algorithms (iv Branch and Bound	Wilke and Ostler(2008)	Solving the school timetabling problem using tabu search, simulated annealing, genetic and branch & bound algorithms
(i) Random Non Ascendant Method (RNA) (ii) Two Variants of Genetic Algorithms	Cadeira-Pena *et al*., (2008)	New approaches for the school timetabling problem
(i) Genetic Algorithms (ii) Immune Systems (iii) Harmony Search, (iv) Tabu Search (v) Simulated Annealing (vi) Great Deluge (vii) Walk Down Jump Up Algorithm	Wilke and Killer(2010a)	comparison of algorithms for solving school and course timetabling problemsusing the Erlangen advanced timetabling system
(i) Genetic Algorithms (ii Genetic Programming	Raghavjee and Pillay(2012)	A comparison of genetic algorithms and genetic programming in solving the school timetabling problem
(i) Integer Programming Approaches (ii)Adaptive Large Neighborhood Search	Sorensen and Stidsen(2013)	Comparing solution approaches for a complete model of high school timetabling
(i) Particle Swarm Optimization Artificial Fish Swarm	Katsaragakis*et al*., (2015)	A comparative study of modern heuristics on the school timetabling problem

3. CONCLUSION AND FUTURE DIRECTION

This article overviewed and surveyed the existing literature on algorithmic approaches for solving school timetabling problems. This review of the algorithmic approachesis a work-in-progress and is by no means exhaustive within the confines of an article. These include early classical heuristic approaches and state-of-the-art approaches including meta-heuristics, constraint-based methods, matheristics, multi-attribute techniques, hybridizations, and recent new trends concerning hyper-heuristics and otheradaptive and knowledge-basedtechniques, which are motivated by raising the generality of the approaches and making them more powerful, efficient and effective.

However, analysis of the surveyed algorithmic approaches indicates that research in school timetabling could take a number of different interesting future directions. Some of these future directions could be geared towards those discussed in Qu et al., (2009). Furthermore, an investigation of the possibilities of solving school timetabling problems using some meta-heuristic techniques such as Stochastic Algorithms (Scatter search), Evolutionary Algorithms (Genetic Programming, Evolutionary Strategies, Evolutionary Programming, Differential Evolution), (PSO, Ant Colony Optimisation), Physical Algorithms (Harmony Search, Cultural Algorithm Memmetic Algorithm), Probabilistic Algorithms, Swarm Intelligence Algorithms, Immune Algorithms,Neural Algorithms, Multi-Criteria and Multi-Objective Approaches, More General and Adaptive Approaches (Case-Based Reasoning, Expert System and Hyper-heuristic).

Finally, extensive study is also required in the areahybridizations of different techniques to integrate different methodologies efficiently particularly between population search-based methods and other approaches in order to provide an appropriate balance between *exploration* and *exploitation* in search algorithms and as well to improve the computational efficiency of search algorithms.

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