Swarm Intelligence For Educational Timetabling: A Survey Of The State Of The Art

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Abstract: Educational timetabling problems regardless of their classification are complex combinatorial problems that face many educational institutions. These problems require the satisfaction of a set of constraints to attain an efficient solution in the matter of resources and time consumption. Swarm intelligence techniques have been successfully applied to solve educational timetabling problems. In this review, the swarm intelligence solutions for solving educational timetabling problems will be investigated and critically discussed. The paper reports the implementation and results of a systematic literature review (SLR) used to collect and highlight the scientific literature on swarm intelligence for educational timetabling. The review links related areas and discusses hot topics on the efficiency of using swarm intelligence, and the gap between academia results and industry implementation in educational timetabling. The paper will be concluded by pointing out and comparing the results obtained in literature. Current promising directions for future research are also presented.

Keywords: educational timetabling; swarm intelligence; scheduling; systematic literature review.

1. Introduction

1.1 What is Swarm Intelligence?

Swarm intelligence is defined by as (Blum and Li 2008) as "An artificial intelligence field concerned with the use and implementation of mutli-agent systems inspired from the natural behavior of social insects such as ants and fish schools". Originally swarm intelligence research is built based on two significant algorithms (David Corne, Alan Reynolds and Eric Bonabeau) firstly, Particle Swarm Optimization (PSO) which was originated by Kennedy and Eberhant (Kennedy and Eberhart 1942, Kennedy 2011) and secondly, Ant Colony Optimization (ACO) which goes back to Dorigo (1991). Both algorithms are one of the earliest swarm intelligence algorithms that had been introduced in the nineties of the last century. The original particle swarm optimization was inspired from the natural behavior of living organisms such as bird flocks, fish school, etc. that interacts within large groups. The swarm consists of a group of particles, each particle establishes a position and moves in the search space with definite velocity, so that each particle can represent a solution in the search space. Particles interact together and create a social network so they can benefit from the experience of each other. Additionally, the fitness function in particle swarm optimization is used to indicate the quality of the solution represented by each single particle. In swarm intelligence these sequences of events differ in their organization from one algorithm to another. Nevertheless, the essence and significance of swarm intelligence algorithms is the same as they all fall under the same umbrella. It's a metaphor where the technique can be based on a group of swarm or colonies and a single solution is represented as particle, ant, bee, or a firefly insect. Therefore, techniques such as particle swarm optimization (Kennedy 2011), ant colony optimization (Dorigo and Stutzle 2003, Blum 2005, Dorigo, Birattari et al. 2006, Dorigo and Socha 2006), artificial bee colony (Karaboga and Basturk 2007, Karaboga, Gorkemli et al. 2014), and firefly algorithm (Yang 2010, Yang 2010, Yang and He 2013, Fister Jr, Yang et al. 2013) have really proven their worth in solving NP-complete problems. Moreover, the literature available today shows that these techniques are very strong and sophisticated enough to be highly competitive.

1.2 The Educational Timetabling Problem

Timetables are essential elements in various areas of life whither in education, work, or transport. Creating a good timetable that satisfies everyone needs is by far a difficult procedure that requires a considerable effort and resources of both people and time. Inefficient timetables could cause problems such as, room clashes and conflict in school and university timetables, railway traffic in train timetables, flights conflict in airline companies and airports, or nurse's shifts conflicts in hospitals. Over the last decade, educational timetabling problems especially those relating to course timetabling and examination timetabling have warranted a considerable amount of researchers' interest. Such complex problems require huge effort and determination to be solved. Providing efficient solutions to these problems require shifting from manual solutions to automated ones. Many artificial solutions have been conducted during the past years, and the existing amount of literature in the field of scheduling and timetabling has contributed a great deal to the timetabling research. Recently the issue of timetabling problem has gained quite a considerable interest which has resulted in the number of available solutions becoming inordinately large and difficult to generalize. Scheduling generally and timetabling in particular are classified as a combinatorial optimization problem (NP-complete problems). Timetabling has different appearance in daily life activities and environments such as in transport (Brännlund, Lindberg et al. 1998, Peeters 2003, Gély, Dessagne et al. 2006, Flier 2011), work (de Werra 1985), (Burke and Petrovic 2002) , and education (Schaerf 1999), (Carter and Laporte 1995, Carter and Laporte 1997). This kind of classification is commonly solved through optimization techniques. Interest in such techniques has been ultimately recognized in the last decade. Moreover, the revolution of meta-heuristics and swarm intelligence techniques have gained the "lion's share" of global recognition in both fields of operational research and computer science.

1.3 Statement of the problem

Achieving optimality in timetabling is a very complicated task which can consume a great deal of time. Therefore, many probabilistic optimization algorithms have been addressed in attempt to solve the timetabling problem. The research in this field is still growing and more efforts are demanded to come up with better solutions. Hence, this research is concerned with the following questions:

- What are the current swarm intelligence solutions for educational timetabling?
- How to improve educational timetabling solutions through swarm intelligence techniques?
- How can real datasets contribute to providing better evaluation for educational timetabling solutions based on swarm intelligence algorithms?

Meta-heuristic is a method for solving very general classes of problems. It usually employs current information gathered by an algorithm to help to decide which alternative solution should be evaluated next, or how the next candidate can be produced. Meta-heuristic methods connect objective functions or heuristics in an abstract form, and hopefully efficient way, neglecting details of an inside structure. If the relation between a solution candidate and its "fitness" is understandable or not too complex, it becomes easier to solve the problem deterministically. Some optimization algorithms are inspired from nature and the behavior of living organisms and swarms e.g. bees swarms, ant swarms, bird flock, fish school, and living colonies. Such algorithms are called swarm intelligence (SI) techniques. (Blum and Li 2008) describes Swarm Intelligence as the design of artificial multi-agents inspired from the collective behavior of social insects and animal societies. (Corne, Reynolds et al. 2012) defines swarm intelligence as the ability of individuals co-operating to achieve a definite goal, i.e. a goal can be in a form of searching and finding nectar in bee colonies, finding the shortest path in ant colonies etc. Meta-heuristics and precisely bio-inspired swarm intelligence algorithms are among the most researched topics in computer science and operational research studies for the last two decades. These algorithms are inspired by the natural behavior of biological systems. Inspired behavior of organisms such as those existing in ants, bees, birds and fireflies has proven its worth in solving real-world complex optimization problems. A review study by (Tang and Wu 2009) focused on the most recent development in biological inspired techniques BIT. The study provided a major classification in three areas of BIT, Evolutionary Algorithms, Swarm Intelligence, and Bacterial Foraging Algorithms. The study concluded that the simplicity of bio-inspired techniques helps in providing a solid ground for creating and adapting methodologies for solving complex problems. Such complex problems as educational timetabling can be solved through Swarm Intelligence approaches. Additionally, this paper presents a systematic review focuses on four well-established swarm intelligence algorithms, namely: Particle Swarm Optimization PSO (Kennedy 2011); Ant Colony Optimization ACO (Dorigo and Stutzle 2003); Artificial Bee Colony ABC (Karaboga and Basturk 2007); and Firefly Algorithm FA (Yang 2010). Most previous surveys focus on heuristics or hyper-heuristics and exact methods approach or rather focus on specific classes of educational timetabling such as course or exam timetabling. Dissimilarly, this review discusses educational timetabling problems generally with respect to swarm intelligence approach.

1.4 Significance of the research

The main contribution of this paper includes an emphasized scientific investigation into highlighting the gap in the area of swarm intelligence utilization and empowerment to solve educational timetabling problems. In addition, the review investigates and illustrates the limitations found in this area of research and proposes promising topics for future research directions. In other words, this paper presents a systematic literature review on the area of swarm intelligence techniques for solving educational timetabling problems. Therefore, it reveals a detailed analysis of the types of instances used in the educational timetabling experiments. The review gives a thorough discussion of how swarm intelligence helps in solving educational timetabling problems and how can researchers link both practice and theory in terms of solutions available. In this paper we present a review of swarm intelligence approaches for educational timetabling problems. We describe the educational timetabling problem and its classifications; we also discuss data formats and instances used in educational timetabling (section 2). Previous surveys are also discussed in the in section 2. In section 3 we discuss the systematic review method used in this paper and its stages. Additionally, we highlights current literature in swarm intelligence implementation for educational timetabling (section 3) as we concentrate on four approaches, particle swarm optimization, ant colony optimization, artificial bee colony, and firefly algorithm. Moreover, results and selected primary studies from collected literature (section 4) and discussion of findings obtained in (section 5). Finally, the conclusion and future research directions (section 6).

2. What is timetabling?

Timetabling is a type of scheduling problem which focuses on allocating the number of events to a predetermined number of time periods. Wren (1996) defined timetabling as "Timetabling is the allocation, subject to constraints, of given resources to objects being placed in space time, in such a way as to satisfy as nearly as possible a set of desirable objectives". According to (Abdullah 2006) "Timetabling problems are a specific type of scheduling problem and are mainly concerned with the assignment of events to timeslots subject to constraints with the resultant solution constituting a timetable". Accordingly the timetabling problem is generally about assigning an action or an activity to a period of time in a way that meets some condition of measure for scheduling (Schaerf 1999). In Addition, some certain terminologies concerning the timetabling problem need to be used, such as the following:

- Timeslot. A period of time in which events are scheduled.
- Event. A scheduled action or an activity e.g. courses.
- Constraint. A condition of measure or restriction for scheduling events, e.g. courses conflict or room capacity.
- Conflict. Collision of events clashing with each other for being scheduled at the same timeslot.

2.1 Timetabling Constraints

Timetable constraints vary from one kind to another; usually they can be divided into two types, namely, hard constraints and soft constraints. The type and number of constraints vary based on the timetabling problem itself. This kind of variation makes the timetabling problem difficult to solve. Hard constraints have a superior priority than soft constraints as they cannot be violated; while on the other hand, soft constraints can be reconciled to a greater extent, and the more of them being satisfied the better. Therefore, a timetable is considered feasible if all of the hard constraints are satisfied (Abdullah 2006). (Corne, Ross et al. 1995) suggested a different way for classifying timetabling constraints as they divided the timetabling constraints into five different categories as follows:

- Unary constraints. This type is concerned with one event, e.g., event n must be scheduled in timeslot x.
- Binary constraints. This refers to pairs of events, e.g., event conflict or event n must be scheduled before event m.
- Capacity constraints. This type refers to room capacity, etc.
- Event spread constraints. This relates to the concern for demands such as university policy for the timetable, etc.
- Agent constraints. This relates to the preference of individuals who use the timetable, e.g., teacher x likes to teach event n on Sunday.

Timetabling is a type of scheduling problems which can all be considered as NP-complete problems. General educational timetabling problems are concerned with assigning a collection of events whether they are lectures of a course or examinations into a predetermined number of timeslots and rooms to a range of specified constraints. Generally, there is a group of events E, and a set of timeslots T in addition to a set of constraints hard and soft C. The timetabling process is accomplished by assigning event E into the timeslot T, with minimum violation of the hard constraints in order to achieve a feasible timetable outcome. Survey by (Schaerf 1999), classifies educational timetabling into three types based on the type of institution school or university and the type of constraints, classes are: school timetabling, course timetabling and examination timetabling respectively. The classification is not quite strict, as (Schaerf 1999) explained that the problem can be broken down into two types only. In this paper we classify educational timetable into two classes: first, based on the type of institution (university, and school timetabling). Second based on the type of event (course, examination timetabling). More details on educational timetabling problems can be found in both (Schaerf 1999, Burke and Petrovic 2002).

2.2 Educational timetabling based on type of event

2.2.1 Course timetabling

(Carter and Laporte 1997) stated that course timetabling can be defined as: “A multi-dimensional assignment problem in which students, teachers or faculty members are assigned to courses, course sections or classes; "events" individual meetings between students and teachers are assigned to classrooms and times”. Course timetabling represents the challenge of assigning a number of courses to a predetermined number of timeslots where several constraints must be taken into account such as room and lecturer availability. (Carter and Laporte 1997) clarified that, in some cases, courses must be distributed in specific ways throughout the working days of the week. This includes giving consideration to including lunch time in the schedule and some courses being taught in more than two timeslots. A feasible timetable in course timetabling can occur once the following hard constraints are satisfied:

- Inability of both teacher and student to attend two courses at the same time.
- Only one course can be scheduled to a timeslot in each room.
- Room capacity should satisfy the requirement features of the assigned course.

Good course timetabling also attempts as much as possible to satisfy the following soft constraints:

- Students should have more than one course in a day.
- Students should not have a course assigned at the last timeslot of the day.
- Students should not have to attend two consecutive courses in one day.

2.2.2 Examination Timetabling

(Carter and Laporte 1995) defined the examination timetabling problem as: “Assigning of examinations to a limited number of available time periods in such a way that there are no conflicts or clashes”. More succinctly (Abdullah 2006) defined examination timetabling as: “Allocating a set of examinations into a limited number of timeslots periods, subject to a set of constraints.” (Burke, Elliman et al. 1995) defined exam timetabling as the scheduling of a number of exams into a limited number of time periods. The examination timetabling constraints vary based on the institutional problem structure. In other words the problem is to assign a number of exams E to a T timeslot with S examination seats available for each timeslot. With minimal violation of soft constraints in order to achieve a feasible and high quality solution. The main issue involved with this type of educational timetabling is that of avoiding conflicts while assigning a number of examinations to a limited number of timeslots and accomplishing a feasible timetable which satisfies both hard and soft constraints. (Abdullah 2006) reported that in hard constraints for the examination timetabling problem it is necessary to ensure that there is enough seating capacity in the examination rooms, and that students are not required to sit for two examinations during the same time period. On the other hand, soft constraints as stated in (Burke, Elliman et al. 1995) are:

1- Students should not be seated for more than one examination in a day.
2- Students should not be seated for two examinations in consecutive timeslots.
3- Each student’s examinations should be spread as equally as possible in the timetable, subject to the following conditions:
   a. Some examinations may only be scheduled in a specific set of timeslots;
   b. Examinations of the same length may be scheduled in the same room;
   c. Examinations must be scheduled in those rooms which are near to the relevant department.
   d. Examinations with questions in common must be scheduled in the same timeslot.

2.3 Educational Timetabling based on the type of institution

2.3.1 University course timetabling problem (UCTP)

(Socha, Knowles et al. 2002) argued that it is very difficult to generalize the university course timetabling problem with one definition because the structure of the course organization and the constraints of the problem differ from one case to another.

Problem description:
The problem consists of a set of courses E to be assigned in a predetermined number of timeslots T = {t1, . . . , tk} k = 45, 5 days × 9 hours, together with: a set of rooms R where events take place each room has a certain capacity; a set of students S who attend the courses; and a set of features F satisfied by rooms and demanded by courses. A timetable can be called feasible if, and only, all hard constraints are satisfied, otherwise it is considered infeasible and viewed as a bad timetable. The main objective is to minimize as much as possible any soft constraints violations in a feasible timetable. (Abdullah 2006) presented a solution having a list of positions with a length N where the position corresponds to the course. For example, position i corresponds to course ei for i = 1… N. Each position has to provide values which are the timeslot and the room respectively. As an example, for number of given timeslots 0, 15, 20,…,10 and rooms 7, 9, 12,…, 3. We see that course e1 is assigned to timeslot 0 at Room 7 and course e2 is assigned to timeslot 15 at Room 9. Finally, course eN is assigned to timeslot 10 at Room 3.

2.3.2 School timetabling

(de Werra 1985) defines school timetabling as “A type of classroom assignment or course timetabling”. (Schaerf 1999) defines school timetabling as “A weekly scheduling for all classes of a school avoiding teachers meeting for two classes at the same time”. (Schaerf 1999) described the problem based on De werra class/teacher model in 1985 stating that the problem is to assign lectures to periods in a way that no clashes happens in teacher or class occupation for a lecture at a time.

Problem description:

- Let C1,… Cm be m classes.
- t1,… tn be n teachers.
- And 1,… p be p periods.
- Rmxn is a non-negative integer matrix, where rij is the number of lectures given by a teacher tj to ci.

Constraints:

- Each teacher gives the number of right lectures to each class.
- Ensure that each teacher is involved in at most one lecture for each period.

2.4 Timetabling Datasets and Instances

In this sub-section, educational timetabling data formats are discussed. A specific and clear explanation is provided with reference to the common datasets used as benchmark for problems of course, examination, and school timetabling.

2.4.1 Course timetabling datasets

There are many datasets in the timetabling community for the course timetabling problem. In this part, the Meta-heuristics Network benchmark, the International Timetabling Competition, and school timetabling datasets are discussed.

2.4.1.1 The Meta-heuristics Network benchmark Socha

The course timetabling problem in this dataset is categorized into three types, small, medium and large. The problem consists of scheduling a number of 100 to 400 courses into a timetable with predetermined 45 timeslots 5 days x 9 hours. The dataset also provides a number of students and room features such as room capacity (Blum, Correia et al. 2002, Socha, Knowles et al. 2002). The following table (1) describes Socha’s dataset instances.

Table (1) *Socha’s dataset instances*

Category	Small	Medium	Large
Number of courses	100	400	400
Number of rooms	5	10	10
Number of features	5	5	10
Number of students	80	200	400
Maximum courses per students	20	20	20
Maximum students per courses	20	50	100
Approximate features pre room	3	3	5
Percentage of feature use	70	80	90

2.4.1.2 The International Timetabling Competition ITC

The first International Timetabling Competition was held in 2002 and was organized by the meta-heuristic network. As a result of its success, the timetabling research community continued with organizing new versions of the competition, the fifth of which was held in 2014. Information regarding the ITC-2002 problem instances and solution evaluation is available from the following webpage: http://www.idsia.ch/Files/ttcomp2002/. The ITC instances gather all types of educational timetables which apply to universities and schools. The datasets are based on simplified real-world problems. For more information about the rules and evaluation of the second international timetabling competition 2007, visit the webpage: http://www.cs.qub.ac.uk/itc2007. ITC divided the course timetabling problem into two types, namely, Curriculum-based course timetabling and Post enrolment-based course timetabling. Both types vary in their constraints and features (McCollum, Schaerf et al. 2010). First, Curriculum-based course timetabling was introduced in the ITC-2007(Di Gaspero, McCollum et al. 2007). Curriculum-based course timetabling consists of assigning lectures of several courses to a set of timeslots within a given number of rooms. In this type, it is important to remember that conflicts between courses are considered with respect to the curricula provided rather than merely data enrollment.

Problem parameters:

- Days, Timeslots, and Periods: We are given a number of teaching days per week typically 5 or 6. Each day is split into a fixed number of timeslots, which is equal for all days. A period is a pair composed of a day and a timeslot. The total number of scheduling periods is the amount of days multiplied by the day timeslots.
- Courses and Teachers: Each course consists of a fixed number of lectures to be scheduled in distinct periods. The course is attended by a specified number of students, and is taught by a teacher. Each course has a minimum number of days over which

the lectures of the course should be spread. Further, there are some periods during which the course cannot be scheduled.

- Rooms: Each room has a specific capacity, expressed in terms of the number of available seats. All rooms are equally suitable for all courses if large enough.
- Curricula: A curriculum is a group of courses arranged so that any pair of courses in the group has students in common.
- Hard constraints:
- Lectures: All lectures of a course must be scheduled, and they must be assigned to distinct periods. A violation occurs if a lecture is not scheduled.
- Room Occupancy: Two lectures cannot take place in the same room in the same period. Two lectures in the same room during the same period represent a violation. Any extra lecture in the same period and room counts as one more violation.
- Conflicts: Lectures for courses in the same curriculum or taught by the same teacher must all be scheduled in different periods. Two conflicting lectures in the same period represent one violation. Three conflicting lectures count as three 3 violations: one for each pair.
- Availabilities: If the teacher of the course is not available to teach that course at a given period, then no lectures of the course can be scheduled during that period. Each lecture in a period unavailable for that course counts as one violation.

Soft constraints:

- Room Capacity: For each lecture, the number of students that attend the course must be less than or equal to the number of seats in all the rooms that host its lectures. Each student above the capacity counts as one 1 point of penalty.
- Minimum Working Days: The lectures of each course must be spread over a given minimum number of days. Each day that falls below the minimum counts as five 5 penalty points.
- Curriculum Compactness: Lectures belonging to a curriculum should be adjacent to each other i.e., in consecutive periods. For a given curriculum, we account for a violation every time there is one lecture not adjacent to any other lecture within the same day. Each isolated lecture in a curriculum counts as two 2 points of penalty.

Table (2) *Curriculum-based course timetabling dataset instances*

Categories	events	periods	rooms	courses	Courses of groups	Lower bound best	Upper bound best
COMP01	160	30	6	30	14	5	5
COMP02	283	25	16	82	70	24	10
COMP03	251	25	16	72	68	66	38
COMP04	286	25	18	79	57	35	35
COMP05	152	86	9	54	139	291	114
COMP06	361	25	18	108	70	27	16
COMP07	434	25	20	131	77	6	6
COMP08	324	25	18	86	61	37	37
COMP09	279	25	18	76	75	96	66
COMP10	370	25	18	115	67	4	4
COMP11	162	46	5	30	13	0	0
COMP12	218	36	11	88	150	300	53
COMP13	308	25	19	82	66	59	48
COMP14	275	25	17	85	60	51	51
COMP15	251	25	16	72	68	66	41
COMP16	366	25	20	108	71	18	13
COMP17	339	25	17	99	70	56	44
COMP18	138	36	9	47	52	62	0
COMP19	277	25	16	74	66	57	49
COMP20	390	25	19	121	78	4	0
COMP21	327	25	18	94	78	83	0

The second type is post enrolment-based course timetabling was first introduced in the ITC-2002 (Lewis, Paechter et al. 2007). The main difference in this type is that the post-enrollment course timetabling problems concentrate on students' preferences such as "a student should only have one course per day"; while curriculum-based course timetabling focuses on lecturers' preferences such as "lecturers only want to have their lectures in the morning".

Problem parameters:

- A set of N courses, e = (e1,...,eN)
- 45 timeslots
- A set of R rooms
- A set of F room features
- A set of M students.

The following represent hard and soft constraints:

- No student can be assigned to more than one course at the same time.
- The room should satisfy the features required by the course.
- The number of students attending the course should be less than or equal to the capacity of the room.
- No more than one course is allowed in each room during each timeslot.

- Soft constraints that are equally penalized are as follows:
- A student has a course scheduled in the last timeslot of the day.
- A student has more than two 2 consecutive courses.
- A student has a single course on a day.

Table (3) *Post enrolment-based course timetabling dataset instances*

Instance	1	2	3	4	5	6	7	8
Event	400	400	200	200	400	400	200	200
room	10	10	20	20	20	20	20	20
feature	10	10	10	10	20	20	20	20
student	500	500	1000	1000	300	300	500	500
Instance	9	10	11	12	13	14	15	16
Event	400	400	200	200	400	400	200	200
room	10	10	10	10	20	20	10	10
feature	20	20	10	10	10	10	20	20
student	500	500	1000	1000	300	300	500	500
Instance	17	18	19	20	21	22	23	24
Event	100	200	300	400	500	600	400	400
room	10	10	10	10	20	20	20	20
feature	10	10	10	10	20	20	30	30
student	500	500	1000	1000	300	500	1000	1000

2.4.2 Examinations timetabling datasets

This part highlight most used datasets in examination timetabling which are Toronto dataset and ITC exam dataset.

2.4.2.1 The Toronto Benchmark

Also named Carter's uncapacitated examination timetabling dataset. This benchmark was first introduced by carter in 1996 and consists of 12 datasets. The dataset problem is described as follows:

- N presents number of exams.
- Ei is an exam, i ∈ {1,. . .,N}.
- T presents number of available timeslots.
- M presents number of students.
- C = (cij)NxN is the conflict matrix, where each element denoted by cij, i,j ∈ {1,. . .,N} is the number of students taking exams i and j.
- tk (1 ≤ tk ≤ T) specifies the assigned timeslot for exam k (k ∈ {1,. . .,N}).

Table (4) *below describes the characteristics of Carter's datasets:*

Instance	1	2	3	4	5	6	7	8
Event	400	400	200	200	400	400	200	200
room	10	10	20	20	20	20	20	20
feature	10	10	10	10	20	20	20	20
student	500	500	1000	1000	300	300	500	500
Instance	9	10	11	12	13	14	15	16
Event	400	400	200	200	400	400	200	200
room	10	10	10	10	20	20	10	10
feature	20	20	10	10	10	10	20	20
student	500	500	1000	1000	300	300	500	500
Instance	17	18	19	20	21	22	23	24
Event	100	200	300	400	500	600	400	400
room	10	10	10	10	20	20	20	20
feature	10	10	10	10	20	20	30	30
student	500	500	1000	1000	300	500	1000	1000

2.4.2.2 The International Timetabling Competition (examination dataset)

This is the third type of datasets presented by ITC which consist of 8 exams timetabling instances presented as follows in table (5):

Table (5) *The International Timetabling Competition exam dataset*

Dataset	Number of students	Number of examinations	Number of timeslots	Number of rooms	Period hard constraints	Room hard constraints	Conflict density
Exam_1	7891	543	54	7	12	0	5.05
Exam_2	12743	682	40	49	12	2	1.17
Exam_3	16439	190	36	48	170	15	2.62
Exam_4	5054	81	21	1	40	0	15.0
Exam_5	9253	461	42	3	27	0	0.87
Exam_6	7909	381	16	8	23	0	6.16
Exam_7	14676	2419	80	15	28	0	1.93
Exam_8	7718	486	80	8	20	1	4.55

2.4.3 School timetabling datasets

There are some projects dedicated to school timetabling datasets in this part we highlight three of them:

- The Greek project: High school datasets taken from 30 different schools in Greek. The datasets are available at http://prlab.ceid.upatras.gr/timetabling/ and are used by (Beligiannis, Moschopoulos et al. 2008)
- Another dataset originally benchmarked by (Abramson and Dang 1993) are available from the OR-library at http://people.brunel.ac.uk/~mastjjb/jeb/orlib/tableinfo.html and contributed by (Smith, Abramson et al. 2003).
- There are other relevant datasets, for example the new High School Timetabling Archive XHSTT. It's a benchmarking project by a group of researchers developed for high school timetabling instances. This dataset contains 21 instances from 8 countries. The format of the dataset is mapped by an XML schema and it's available at http://www.utwente.nl/ctit/hstt.

2.5 Previous Surveys

Several surveys have been conducted in the area of educational timetabling. The following section critically reviews their contribution and limitations. A widely recognized survey by (Lewis 2008) describes the graph coloring approach in a new classification to the problem of educational timetabling. Lewis provides a classification for metaheuristics-based approach. Classes are namely, one stage optimization, two stage optimization, and algorithms that allow relaxation. (Pillay 2012) introduced a general survey of the approach of Hyper-heuristics for solving educational timetabling. The survey mainly focuses on providing a general solution to the educational timetabling problem through Hyper-Heuristics rather than solving a particular timetabling problem. However, the author significantly notices that Hyper-Heuristics available studies are mostly dedicated to solve examination timetabling. (Pillay 2014) describes the school timetabling problem in a review study where she discusses the methodologies and approaches used to solve the school timetabling problem. Moreover, she highlights school timetabling datasets and the importance of industrial and academic work in developing school timetabling systems. (MirHassani and Habibi 2013) discusses the approaches used to solve the course timetabling problem. The survey highlights the most frequently used techniques such as genetic and memetic algorithm GMA, simulated annealing SA, tabu search TS, graph coloring algorithm GCA and mixed integer programming MIP. (Kristiansen and Stidsen 2013) discusses the recent trends in educational timetabling. Primarily he focuses on educational planning problems with respect to timetabling. He divides his study into four planning problems: high school timetabling, university course timetabling, examination timetabling, and student sectioning. He also highlights the gap between practice and theory in timetabling development and generalizing benchmarks data. (Babaei, Karimpour et al. 2015) analyses several approaches applied to university course timetabling problem UCTP. He particularly focuses on multi agent system as a new approach to solve UTCP. (Katsaragakis, Tassopoulos et al. 2015) describes the different approaches of modern Heuristics techniques for school timetabling problem. Particularly, he studies and compares two population-based techniques, PSO and Artificial Fish swarm. (Fernandes, Pereira et al. 2016) surveys the application of Bullet timetabler education BTTE and its success in educational timetabling problem over almost all Portuguese schools of higher education. He discusses the timetabling problem from a decision support approach point of view and emphasizes the ability of this approach to reduce costs in real educational institutions. (Pandey and Sharma 2016) provides a survey on university timetabling problem. The author describes different types of methods such as ACO, hybrid bee colony optimization, PSO, and genetic algorithm. (Vrielink, Schepers et al. 2016) presents a systematic review concerning timetabling in Higher Educational Institutions HEI. He mainly focuses on HEI structure and practices especially on environmental characteristics. The review classifies the solution approaches into timetabling application development and timetabling algorithms development.

3. Systematic Literature Review Method

A systematic literature review SLR has been performed for the purpose of this study. This section, describes the design of the SLR and how it was used to attain the research objectives. A systematic literature review SLR, or systematic review, differs from traditional reviews in that it is a form of literature review that collects and looks at multiple studies. It is a way of extracting useful information from a large number of different studies and databases so as to contribute and provide answers to a precise research question related to the study field. The SLR will produce the following results: 1) provide a full background on the educational timetabling problem; 2) find any literature gaps in order to facilitate future improvements; 3) provide a critical discussion on educational timetabling instances and experiments.

3.1 Systematic Review Stages

Generally, and according to (Kitchenham 2004) systematic reviews are accomplished in three stages: planning, conducting, and reporting. Due to the nature of the research the researcher designed the breakdown of the stages as shown in figure .1 below. The figure breaks the same stages into more detailed ones which are followed to perform this systematic review.

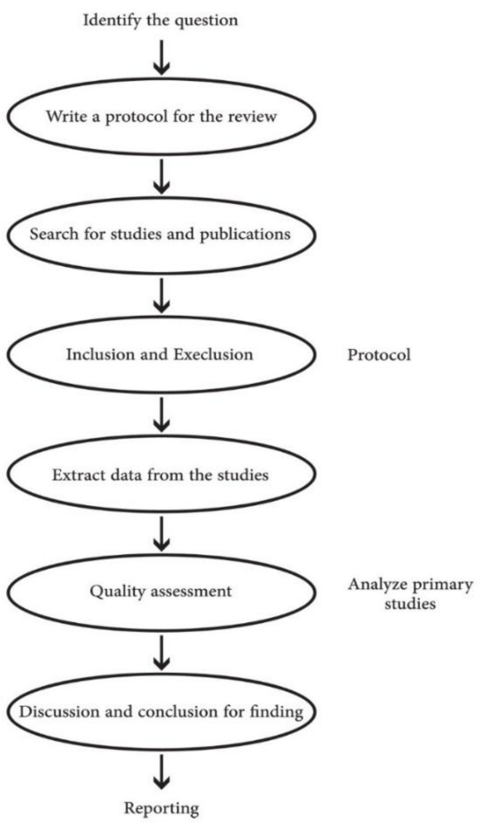

Figure 1.

The systematic review SLR is guided by mainly three forms of research questions presented as follows:

- What are the recent optimization based approaches for solving educational timetable problems and how can they be evaluated?
- What are the current and future trends, directions and gaps to be filled by future researchers?
- What types of common issues face researchers in the field of educational timetabling?

3.2 Inclusion and Exclusion Criteria (systematic review protocol)

The systematic review protocol specifies the methods and criterion that will be used to undertake the systematic review. Inclusion and exclusion criteria help in the process of extracting studies related to the SLR topic and abandoning the rest of the collected database. The following table (6) describes the type of criteria used in the SLR:

***Table (6)** inclusion and exclusion criteria*

Criteria	Details
Types of studies	Experimental studies.
Field	Educational timetabling, optimization, swarm intelligence ACO, ABC, PSO, FA.
Date of publication	2010- 2017.
Publication language	English
Database and journals	Google Scholar, IEEE, Elsevier, Springer

3.3 Literature search process

For the literature search process in SLR literature data collection is the process of finding pertinent literature driven by a specific search strategy used for gathering papers from journals and conferences placed in known databases which includes IEEE XPlore, Google Scholar, Elsevier and Springer Digital Library. Specific keywords must be identified and then used to obtain best results in the area of research.

3.3.1 Data collection

The researcher carried a literature search process whereby he identified key words which are: timetable optimization, timetabling, timetable scheduling, scheduling optimization, educational timetabling optimization, timetable problem, educational timetable problem, timetable problem optimization, course timetabling, course timetabling optimization, examination timetabling, examination timetabling optimization, combinational optimization, PSO timetabling, particle swarm optimization timetabling, artificial bee colony optimization timetabling, ABC timetabling, Ant colony timetabling, ACO timetabling, and finally, Firefly algorithm timetabling. The following sub-section present a collection of the systematic review collected literature focused on using swarm intelligence (SI) techniques to solve different types of educational timetabling problems. The literature has passed the first screening criteria presented in table 6. The data is categorized based on the type of SI technique used.

3.1.2 Particle Swarm Optimization PSO

"Particle Swarm Optimization was introduced by kenndy and ebrehant in 1995. PSO is inspired from the social behavior of birds flocking. Its idea is based on how can birds fly in large group and maintain optimum distance between themselves and their neighbors" A study by (Chu, Chen et al. 2006) applies PSO to solve discrete problem of examination timetable. The problem consisted of three versions: 11 exams, 13 exams, and 15 exams. The experiment measures the quality of the solution by giving each constraint a penalty or weight and the experiments demonstrated that PSO is an efficient technique for solving discrete timetabling problems. Moreover, no clash happened in the timetabling scheduling. (Shiau 2011) Presents a hybrid approach based on particle swarm optimization to solve the university course timetabling problem. The hybrid approach provides some features such as improving the particle position value. Also giving the instructor the ability to lecture based on flexible preferences (preferred days and timeslots). The technique was tested on data taken from a university in Taiwan. The results obtained shows that the approach is able to provide an efficient solution. Moreover the results of the study outperformed genetic algorithmic technique. (Tassopoulos and Beligiannis 2012) developed a PSO algorithm for solving school timetabling problem. This algorithm was then tested on real-world data taken from different high schools in Greece. Several experiments were conducted in this study. The PSO algorithm performance was compared with other similar studies which used different algorithms such as Genetic Algorithm GA and Evolutionary Algorithm. The comparison was based on three criterias, Firstly the teacher teaching hours distribution, secondly the lesson hours distribution, and thirdly the teacher's gaps. The results obtained showed that PSO outperformed other approaches in 13 out of 18 cases which equals 72%, also they had the same best results in 3/18 cases. However, worse results were reported in overly 2 of 18 cases, which is 11%. Additionally, the study continues the experiments by comparing their results with other approaches. The result obtained demonstrated that PSO outperformed other algorithms in 8 of 12 cases which is 66.7% and had same best results in 3 of 12 cases and recorded worse results in 1 of 12 cases 8.3%. Based on these comparisons it was clear that the proposed PSO algorithm proved to be very efficient approach to solve school timetabling problem. (Tassopoulos and Beligiannis 2012) continued experimenting PSO in another study focusing on solving high school timetabling problem. In this experiment the author proposed a hybrid PSO based on the basic PSO algorithm and the use of local search procedure which helped in improving the quality of the generated solution. The algorithm was tested on real-world data taken from different high schools in Greece. The results obtained showed that the proposed hybrid PSO gave better results when compared with similar studies contained in respective literature. (Adrianto 2014) compares PSO performance in timetabling scheduling with Genetic Algorithm GA on software laboratory center SLC data. The experiment utilized a swarm consists of 10 particles and a population of 200 pieces of chromosome. The results showed that penalty obtained by PSO is quite smaller than GA, which indicates that PSO provides better optimality. Moreover, PSO implementation used a less number of iterations unlike GA. In a survey by (Marie-Sainte 2015) the implementation of PSO for solving examination timetabling was also discussed. Larabi concluded that the use of PSO in this problem begins with representing a particle as whole timetable which means assigning a number of exams to a defined number of timeslots and rooms. The fitness of each solution is measured either by the number of violations in the exam timetable or summing penalties of soft constraints. However, PSO alone is not enough to gain an optimized timetable therefore the need for hybridization accrues. It is important using PSO with local search techniques which helps in gaining a feasible timetable. (Marie-Sainte 2015) demonstrated that PSO is a stochastic optimization technique for solving examination timetabling and his survey showed that PSO implantation to examination timetabling is quite limited in the current literature. He concluded by pointing out that PSO is a very common meta-heuristic technique which is suitable for complex constrained problems. Nevertheless, a quite few articles in literature dedicated PSO to solve this problem.

3.1.3 Ant Colony Optimization ACO

"Ant Colony Optimization algorithm is one of the most well-established and famous swarm intelligence algorithms introduced by Dorigio in late 80's and originally used to solve discrete optimization problems. ACO is inspired from the social behavior of ant colonies and how ants find the shortest route between their food and their nest" Ant colony optimization is another swarm intelligence technique discussed in this research. Back in 2002 (Socha, Knowles et al. 2002) presented the Max-Min Ant System to solve the university course timetabling problem UCTP. The experiment was based on the work of The Meta-Heuristic Network. The problem instances consisted of three UCTP classes. The results obtained showed that ant system is able to solve hard constrained problems and with use of local search it was possible to generate better solutions. Additionally the proposed Max-Min Ant System algorithm proved to be quite competitive with other meta-heuristics solutions in The Meta-Heuristic Network. In 2003 (Socha, Sampels et al. 2003) compared the performance of Ant Colony System with Max-Min Ant System. The experiment was conducted on instances from three classes varying in size: small, medium, and large. The results were compared and it was clear that the performance of both techniques was very different. The Max-Min Ant System MMAS performance was better than Ant Colony System ACS on the three tested classes, especially on large instances Max-Min Ant System was better than any other competitor at that time. (Socha, Knowles et al. 2002) highlighted the reasons for the different performance of the Ant algorithms. i.e. MMAS doesn't use heuristic information, unlike ACS which uses a lot of heuristic information. Moreover, ACS uses a different strategy in local search than MMAS, specifically ACS goes through the local search for a number of steps, but for MMAS it tries to reach local optima by defining extensive number of steps. Moreover, ACS tries to improve the generated solutions, unlike MMAS which uses local search to only improve one solution generated. (Ejaz and Javed 2007) solves Socha's timetabling dataset using a Die-Hard Co-operative Ant technique. The approach is different from regular Ant colony algorithm, the technique is inspired from mutual aid and persistent and cooperative behavior. When food is found an ant take it alone, if its heavy more ants are activated to pick it up. If the food is too heavy ants breaks into pieces. The technique Ejaz presents provide very competitive results with others in literature at the time. Although the Ant Colony alone has showed great results in solving educational timetabling problems, the use of hybridization has demonstrated a much more advanced results. (Ayob and Jaradat 2009) presented two hybrid techniques, the simulated annealing with ant colony, and tabu search with ant colony. Both techniques were used to solve the university course timetabling. The experiment was conducted on Socha's benchmark instances. The results obtained by this study (Ayob and Jaradat 2009) outperformed the MMAS (Socha, Knowles et al. 2002). However, both techniques succeeded in the case of small instances but failed to show similar success in medium and large instances. Jaradat and Masri Ayob continued experimenting Ant algorithm for solving educational timetabling (Jaradat and Ayob 2010). They presented An Elitist-Ant System for solving post-enrollment course timetabling problem which is taken from Socha's dataset (Socha, Knowles et al. 2002). The proposed approach was first presented by (Gambardella, Taillard et al. 1999) to solve course timetabling problem. The approach follows two mechanisms, intensification and diversification. Intensification is used to explore the neighbor of good solutions in order to improve the best solution found. As for diversification mechanism it is used after preforming a number of defined iterations to help in avoiding early algorithm convergence, It is also used to erase all pheromone trails periodically. Both mechanisms helped in improving the Ant System in search space. The results obtained were compared with other similar population-based approaches in literature. The proposed algorithm did provide feasible timetable in all tested instances. And it gave optimal solution especially in small instances. Another study utilized Ant Colony Optimization ACO to solve the Post Enrollment Course Timetabling Problem (PECT) which is taken from The International Timetabling Competition ITC2007. In this experiment (Nothegger, Mayer et al. 2012) presented a new approach to solve PECT. The experiment highlighted the significance of utilizing local search with ACO. However, the new approach employed another technique namely Best First Ejection Chain Improvement (Glover 1992). This technique helps in moving events causing soft constraints violations to a different timeslot without violating hard constraints. Furthermore, if an event needed to be removed the chain continues by replacing the event. The algorithm gave high quality results even without the use of local improvement method, and the solution proposed ranked 4th among all solution presented in ITC2007. Similarly (Thepphakorn, Pongcharoen et al. 2014) addressed new methods to improve ACO performance. His study proposed using other variants of ACO to solve course timetabling problem. Methods proposed were, namely Best-Worst Ant System BWAS and Best-Worst Ant Colony System BWACS. Both methods used local search for more efficiency in finding optimal solutions. The experiment was conducted on eight instances of course timetabling problem selected from the ITC2007. Both methods showed better results in term of solution quality and speed than the original ACO.

3.1.4 Artificial Bee Colony ABC

"a swarm intelligence technique proposed by Karaboga in 2005. The technique is inspired from the intelligent behavior of honey bee swarm. The artificial bee colony contains three groups of bees: employed bees: bees that visit the food source, onlooker bees: bees that wait in the dance area to choose a food source, and scout bees: bees that search randomly for food source" (Bolaji, Khader et al. 2011) presented an Artificial Bee Colony ABC algorithm for solving curriculum-based timetabling problem which is taken from the International Timetabling Competition ITC2007. The study proposed using a method named Saturation Degree SD to obtain a feasible solution. However, the results of the study were not better than the previous studies due to the problem of local optima. Using ABC algorithm (Junaedi and Maulidevi 2011) attempted solving a curriculum-based course timetabling problem. The study utilized the basic ABC with no further modification or hybridization. The experiment was conducted on 21 instances taken from the ICT2007 and each data instances was run 10 times using different parameters. However, the algorithm did not produce better performance than already existing literature especially in comparison with (Bolaji, Khader et al. 2011). Asaju Bolaji improved the performance of ABC algorithm in another study (Bolaji, Khader et al. 2012) using the effect of neighborhood structure for solving examination timetabling problem. The neighborhood structure begins with initializing a solution and then gradually the technique explores the neighborhood of the solution for further improvements. ABC uses two types of operators namely onlooker and employed bees in which they use three different neighborhood structure to explore the search space in order to find better solution. The three neighborhood structure are move, swap, and kemp chain. The experiment was conducted on carter's datasets. From the result obtained it was clear that using the neighborhood structure did improve the performance of ABC algorithm compared with similar studies in literature. In another study Asaju Bolaji experimented hybridizing ABC algorithm with Hill Climbing Optimizer for solving university course timetabling problem (Bolaji, Khader et al. 2014). The experiment was conducted on Socha's dataset (Socha, Knowles et al. 2002). The proposed approach used saturation degree SD and Backtracking algorithm BA after the initialization phase. Hill climbing is a local search technique and it helps in finding local optima. The results obtained showed that using hill climbing with lower value generally enhanced the generated solution. The study concluded that hybridized ABC succeed in providing feasible timetable. Moreover, the solution generated had no constrains violations for all types of dataset, small, medium and large. Additionally, the proposed hybridization obtained high quality solution compared with other similar studies in literature. (Alzaqebah and Abdullah 2015) presented a hybrid bee colony optimization algorithm BCO to solve the examination timetabling problem. The hybridization conducted was done in three types, selection strategy, self-adaptive mechanism, and local search algorithms. Furthermore, three types of selection strategies were embedded within BCO which were: disruptive selection, rank selection, and tournament selection. From the experiment results disruptive BCO DBCO did outperform basic BCO and the two other types of selection strategies. The Second experiment ran DBCO with self-adaptive mechanism which was compared with DBCO and the results showed that self-adaptive mechanism provided better performance because it helped in selecting the neighborhood structure to explore the search space which in turn helped in finding a better solution. Moreover, the third experiment hybridized self-adaptive DBCO with local search algorithms namely simulated annealing and local search. The experiment indicated that both local search algorithms helped in obtaining better solutions. Consequently, using local search helped in avoiding local optima. However, hybridized DBCO with local search algorithm did outperform DBCO with simulated annealing. Finally, self-adaptive DBCO did prove to be a strongly competing technique with other approaches available in literature as it provided best new results in both carter's and ICT2007 datasets.

3.1.5 Firefly Algorithm

"Firefly algorithm was originated by Xin She Yang in 2008. It's inspired for the social behavior of fireflies insects."

During the search process the researchers found no references or any evidence support that firefly algorithm had been used in educational timetabling. Therefore, there is no available literature concerning this technique in educational timetabling.

4. Results and Analysis

In this section the systematic review protocol is implemented to select primary studies out of collected scientific literature. Moreover, the final results of the systematic review and its investigation findings are presented as well. As a conclusion to the search process it is clear that conducting research in the field of educational timetabling and specially those implemented swarm intelligence techniques have raised since late nineties and precisely since 1995 see figure (2). Although the number of publications in this scope is quite limited as it is presented by figure (2), the number of publications did increase gradually though with low race. Furthermore, years from 2010-2017 have witnessed the highest percentage in number of publications concerning swarm intelligence approaches i.e. PSO, ACO, ABC OR BCO in educational timetabling. Nevertheless, this percentage needs to be enhanced. As some of these techniques like Firefly Algorithm have never been used in educational timetabling problems.

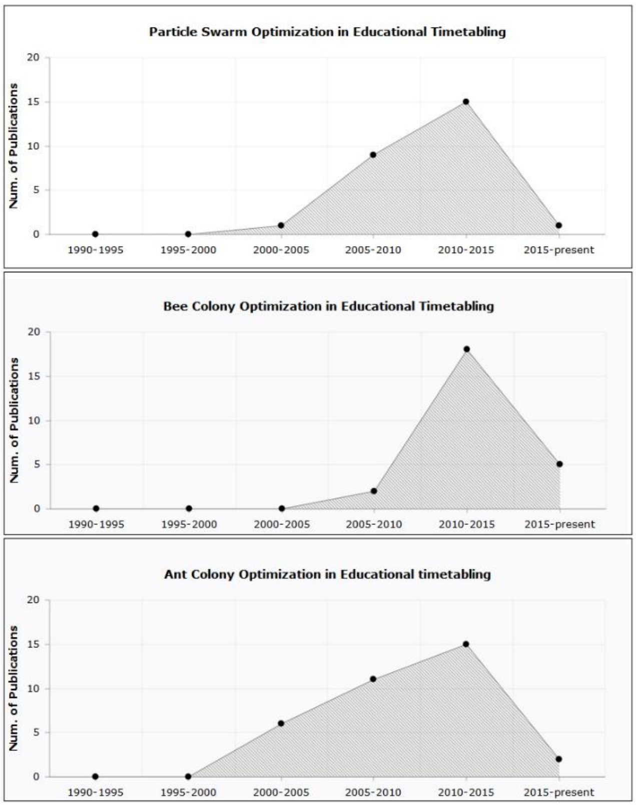

Figure (2) *below shows the raise in number of publications in educational timetabling solved using swarm intelligence techniques since 1990 up to 2017.*

As a result, it was possible to collect a total of 153 studies see table (7). With the use of the SLR protocol, the studies were reviewed. The number of studies was restricted and only 24 papers fell in the scope of the protocol, which is 15.68% out of the collected studies.

Table (7) *shows the number of collected papers form different databases*

Database	Number of finding
IEEEXplore	23
Springer	22
Elsevier	13
Else	95
Total	153

4.1 Quality Assessment

In addition to the inclusion and exclusion criteria, the selected primary studies went through a description and a classification process. In this process, the SLR investigation goes deeper and the strength of the chosen studies is revealed to assess its quality. The assessment helps in gathering the findings and determining the gaps moreover, weighting the strength and importance of each study. A selected number of questions were provided to be answered for each study during the data extraction process see Table (8).

Table (8) *shows the results obtained from quality assessment questions*

ID	Quality assessment questions	Yes	No
QA1	Is the aim of the research sufficiently explained?	100%	0
QA2	Is the presented idea clearly explained?	100%	0
QA3	Are the findings of the research clearly stated?	95.8%	4.2%
QA4	Is it clear which technique was used?	95.8%	4.2%
QA5	Is it clear how the technique was used?	91.7%	8.3 %
QA6	Are threats to validity or limitation reported?	83.3%	16.7%
QA7	Do the publications use more than one dataset?	50%	50%
QA8	Do the publications use more than one evaluation measure?	54.2%	45.8%

In QA1, it was relatively easy to assess if each study distinctly clarified its aim and goal, and this question was answered positively for all reviewed studies. QA2 assessed whether the studies explained the proposed idea clearly. This question also returned a full positive answer for the reviewed studies. With QA3, it was possible to determine if all studies transparently stated their respective results and findings. The result of this question was 95.8% for positive answers, while 4.2% answered negatively. QA4 asked if the technique used to overcome the problem of the study was clearly stated. A total of 95.8% answered positively, leaving the remaining 4.2% with a negative answer. QA5 enquired how the selected technique was used and implemented. A total of 91.7% of the studies gave a positive answer; while 8.3% replied with a "No". QA6 enquired as to whether threats to validity and limitation were reported. A total of 83.3% answered with yes; while 16.7% answered with "No". In QA7, the studies were assessed for using more than one timetabling dataset. The result were equal for both positive and negative answers. In the final question QA8, the aim was to investigate the number of evaluation measures used in the studies. It was found that 54.2% used more than one measure and 45.8% used either one measure or none.

4.2 Threats to Validity and Limitation

Validity threats and the associated risk in affecting the accuracy of the conducted research is an important factor that needs to be taken into account. The main threats discussed in this section are publication bias and data extraction respectively. Although the number of used keywords was intentionally chosen to be large considering that it would ensure better retrieval results for the studies, this consideration had some consequences. These included the appearance of researches related to the collected studies i.e. online published PhD and masters' thesis's concerning the same research problem. In order to reduce the search bias, the actual search was followed by another one in multiple search engines such as: Researchgate and Google scholar, this helped to minimize the threat. Another threat posed was the data extraction stage. The issue concerned the numerous optimization techniques used in the primary studies. Furthermore, the techniques used were not only utilized to overcome the research problem; but also, the researchers had to review the primary studies multiple times in order to understand which techniques were being used for solving the research problem timetabling. Eventually, number of papers was increased to 27 papers which were selected for the final review. See table (9).

4.3 Selected Primary Studies

The following table (9) below provides a brief summary on the selected primary studies.

No.	Reference	Paper title	source	Publication date	method	Study Summary
	(Oswald 2013)	Novel Hybrid PSO algorithms with Search Optimization strategies for a University Course Timetabling Problem	IEEEXplor	2013	PSO	A novel method of solving the UCTP through various Hybrid Search Optimization algorithms combined with Particle Swarm Optimization PSO such as LBS & ATS.
	(Ilyas and Iqbal 2015)	Study of Hybrid Approaches used for University Course Timetable Problem (UCTP)	IEEEXplor	2015	-	Different hybrid state-of-the-art techniques and their use for university course timetabling problems are investigated in this study. There is also an analysis of the occurrence of constraints and their ratio of similarity in recent research trends on university course timetabling problems.
	(Aziz, Taib et al. 2010)	The Effects of Room Slot Address (RSA) Selection Technique in a Modified PSO Algorithm to Solve Class Scheduling Problems	IEEEXplor	2010	PSO	A study is conducted of the Room Slot Address RSA selection technique with three variations, namely, Random RSA selection, Earliest RSA selection and Semi-Random RSA selection techniques in class scheduling problems.
	(Ghasemi, Moradi et al. 2015)	Integrating ABC with genetic grouping for university course timetabling problem	IEEEXplor	2015	ABC	A novel genetic grouping approach using techniques obtained from study of an artificial bee colony is used to find a feasible solution for the university course timetabling problem.
	(Khang, Phuc et al. 2011)	The Bees Algorithm for A Practical University Timetabling Problem in Vietnam	IEEEXplor	2012	Bees Algorithm	The Bees algorithm is applied in an attempt to solve a highly constrained real-world university timetabling problem in Vietnam.
	(Al-Betar, Khader et al. 2012)	University Course Timetabling Using a Hybrid Harmony Search Metaheuristic Algorithm	IEEEXplor	2012	-	A memetic computing technique that is designed for university course timetabling problem is proposed and is called the hybrid harmony search algorithm HHSA.
	(Aziz, Taib et al. 2010)	Acceptance Strategy in a Modified PSO Algorithm to Elevate Local Optima in Solving Class Scheduling Problems	IEEEXplor	2010	PSO	An assignment acceptance strategy in a Modified PSO Algorithm is proposed to elevate local optima in solving class scheduling problems.
	(Aziz, Taib et al. 2010)	The effects of Event Selection based on Soft Constraint Violation (ESSCV) in a Modified PSO Algorithm to Solve Class Scheduling Problems	IEEEXplor	2010	PSO	A local search heuristic which handles event selection is suggested, namely, Event Selection based on Soft Constraint Violation ESSCV. This is applied in a modified PSO algorithm to solve class scheduling problems.
	(Ahandani, Baghmisheh et al. 2012)	Hybrid particle swarm optimization transplanted into a hyper-heuristic structure for solving examination timetabling problem	Swarm and Evolutionary Computation – Elsevier	2012	PSO	The use of discrete particle swarm optimization DPSO is investigated for solving examination timetabling problems.
	(Thepphakorn, Pongcharoen et al. 2014)	An ant colony based timetabling tool	International Journal of Production Economics - Elsevier	2014	ACO	New variants of ant colony optimization called the best-worst ant system BWAS and the best-worst ant colony system BWACS are used for examination timetables.
	(Lutuksin and Pongcharoen 2010)	Best-Worst Ant Colony System Parameter Investigation by Using Experimental Design and Analysis for Course Timetabling Problem	IEEEXplor	2010	ACO	A new variant of Ant Colony optimization called Best-Worst Ant Colony System BWACS is used to solve university course timetabling problems.
	(Bolaji, Khader et al. 2011)	An improved Artificial Bee Colony for Course Timetabling	IEEEXplor	2011	ABC	The ABC algorithm used for tackling Curriculum-Based Course Timetabling Problem CBCTT has been improved.
	(Koshino and Otani 2013)	Constraint Propagation + Ant Colony Optimization for Automated School Timetabling	IEEEXplor	2013	ACO	Hybridization of the ant algorithm for automated school timetabling. These include: Really Full Look-ahead + Ant Colony Optimization RFL+ACO; a constraint propagation-based timetabling algorithm; and Really Full Look-ahead Greedy RFLG.
	(Fong, Asmuni et al. 2015)	A Hybrid Swarm-Based Approach to University Timetabling	IEEEXplor	2015	ABC	Application of an automated hybrid approach in addressing the university timetabling problem. The approach described is based on the nature-inspired artificial bee colony ABC algorithm.

No.	Reference	Paper title	source	Publication date	method	Study Summary
	(Alzaqebah and Abdullah 2011)	Hybrid Artificial Bee Colony Search Algorithm Based on Disruptive Selection for Examination Timetabling Problems	Springer-Verlag	2011	ABC	The ABC algorithm and disruptive selection strategy for onlooker bees, the diversity of the population and the premature convergence has been improved. Further, a local search i.e. simulated annealing is also introduced, in order to attain a balance between the exploration and exploitation processes.
	Saeid Agahian, Huseyin Pehlivan, Rahim Dehkharghani	Adaptation and Use of Artificial Bee Colony Algorithm to Solve Curriculum-based Course Time-Tabling Problem	IEEEXplor	2014	ABC	A new approach, identified as MABC based on the artificial bee colony (ABC) to solve curriculum-based course timetabling problem. The dataset used taken from the ITC-2007 track 3.
	(Bolaji, Khader et al. 2013)	Artificial Bee Colony Algorithm for Post-enrolment Course Timetabling	Springer-Verlag	2013	ABC	A modification to the ABC algorithm for post-enrolment course timetabling problems. The modification is embedded in the study of the behavior of the onlooker bee where the multi swap algorithm is used to replace its process.
	(Sabar, Ayob et al. 2012)	A honey-bee mating optimization algorithm for educational timetabling problems	European Journal of Operational Research – Elsevier	2012	Honey-bee mating algorithm	A honey-bee mating optimization algorithm has been proposed for solving educational timetabling problems.
	(Zou, Qian et al. 2010)	Based on Discrete Particle Swarm Algorithm and Simulated Annealing Algorithm to solve Course Timetabling Problem	IEEEXplor	2010	PSO	A combined discrete particle swarm algorithm and simulated annealing algorithm have been proposed to settle course timetabling problems.
	(Nothegger, Mayer et al. 2012)	Solving the post enrolment course timetabling problem by ant colony optimization	Ann Oper Res – Springer	2012	ACO	An ant colony optimization technique is used to solve the post-enrollment course timetabling problem. The solution proposed ranked 4th in ITC2007
	(Jaradat and Ayob 2010)	An Elitist-Ant System for Solving the Post-Enrolment Course Timetabling Problem	Springer-Verlag	2010	ACO	An Elitist-Ant System for solving the post-enrolment course timetabling problem, the technique proposes to mechanisms namely diversification and intensification which they helps in guiding the search process in the ant system.
	(Tassopoulos and Beligiannis 2012)	particle swarm optimization based algorithm for high school timetabling problems	Applied Soft Computing – Elsevier	2012	PSO	A hybrid particle swarm optimization technique is applied to solve high school timetabling problems in Greek high schools.
	(Tassopoulos and Beligiannis 2012)	Solving effectively the school timetabling problem using particle swarm optimization	Expert Systems with Applications - Elsevier	2012	PSO	A particle swarm optimization algorithm is developed to solve timetabling problem in Greek's high schools
	(Marie-Sainte 2015)	A survey of Particle Swarm Optimization techniques for solving university Examination Timetabling Problem	Artif Intell Rev – Springer	2015	PSO	A survey of PSO techniques applied to solve university examination problems, the paper focuses on selected key papers in this research domain.
	Asaju La'aro Bolaji, Ahamad Tajudin Khader, Mohammed Azmi Al-Betar, Mohammed A. Awadallah , J.Joshua Thomas	The effect of neighborhood structures on examination timetabling with artificial bee colony	Springer (PATAT)	2012	ABC	Artificial bee colony is used to solve the university examination timetabling problem (UETP) using a defacto dataset established by Carter in 1996. In this study the effect of three neighborhood structures is studied which are employed: move, swap and Kempe chain.
	Nelishia Pillay	A survey of school timetabling research	Springer - Ann Oper Res	2013	-	In this survey school timetabling problems and their solution approaches are discussed. Moreover, details of datasets which are publicly available and new direction for further research are presented.
	Hamed Babaei, Jaber Karimpour, Amin Hadidi	A survey of approaches for university course timetabling problem	Elsevier - Computers & Industrial Engineering	2015	-	This paper analyzes current available approaches for university course timetabling problems. It disuses meta-heuristics algorithms and some swarm intelligence techniques such as ant colony optimization and artifice bee colony.

4.4 Best results obtained by swarm intelligence techniques in educational timetabling

In this sub-section results obtained in collected literature are highlighted for comparison. The results are presented in three groups, first results for solving the course timetabling problem, second for solving the problem of examination timetabling, and finally results for solving curriculum-based course timetabling problem. Table (10) below shows the performance of different swarm intelligence techniques used for solving the problem of course timetabling taken from socha's dataset. The best results are in bold. Best results obtained using the technique of honey bee mating which outperformed all other swarm intelligence techniques.

Table (10) *results obtained from swarm intelligence techniques for solving the problem of course timetabling taken from socha's dataset*

Instance	M1	M2	M3	M3	M4	M5	M6	M7	M8
small1	1	5	**0**	**0**	**0**	**0**	**0**	**0**	**0**
small2	3	5	**0**	**0**	**0**	**0**	**0**	**0**	**0**
small3	1	3	**0**	**0**	**0**	**0**	**0**	**0**	**0**
small4	1	3	**0**	**0**	**0**	**0**	**0**	**0**	**0**
small5	0	0	**0**	**0**	**0**	**0**	**0**	**0**	**0**
medium1	195	176	117	150	84	75	73	**52**	57
medium2	184	154	121	179	82	88	79	**45**	54
medium3	248	191	158	183	123	129	132	**96**	114
medium4	164.5	148	124	140	62	74	69	**52**	74
medium5	219.5	166	134	152	75	64	61	**56**	64
large	815.5	798	645	750	690	523	462	**461**	502

- M1: Max-Min ant system (Socha, Knowles et al. 2002).
- M2: Die-hard Co-operative Ant Behavior (Ejaz and Javed 2007).
- M3: Hybrid Ant Colony System (Ayob and Jaradat

2009).
- M4: Elitist-Ant System (Jaradat and Ayob 2010).
- M5: honey-bee mating optimization algorithm (Sabar, Ayob et al. 2012).
- M6: hybridized artificial bee colony with hill climbing optimizer (Bolaji, Khader et al. 2014).
- M7: hybrid imperialist swarm-based optimization algorithm (Weng and Bin Asmuni 2013).
- M8: Hybrid Swarm Based Approach (Fong, Asmuni et al. 2015).

Table (11) below presents the results obtained by different swarm intelligence techniques used for solving the problem of examination timetabling. Instances taken from Carter's uncapacitated dataset. The best results are highlighted in bold font. Techniques such as Artificial Bee Colony, Bee Colony optimization, and Honey bee mating provided superior results in different instances which outperformed all other techniques.

Table (11) *results obtained from swarm intelligence techniques for solving the problem of examination timetabling*

Instance	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11
Car-f-92	5.40	5.70	4.79	5.42	4.67	5.38	5.10	4.71	5.00	4.79	**4.38**
Car-s-91	4.20	4.80	3.90	4.84	5.22	4.61	4.42	3.77	4.22	3.89	**3.88**
Ear-f-83	34.20	36.80	34.69	37.54	35.74	38.58	34.56	**33.15**	38.08	33.43	33.34
Hec-s-92	10.40	11.30	10.66	11.21	10.74	11.17	10.62	10.38	**10.32**	10.49	10.39
Kfu-s-93	14.30	15.00	**13.00**	15.13	14.47	14.89	14.12	13.69	13.91	13.72	13.23
Lse-f-91	11.30	12.10	**10.00**	12.06	10.76	11.74	11.15	10.25	11.04	10.92	10.52
Sta-f-83	158.03	157.20	**157.04**	157.52	157.10	157.21	157.25	157.03	157.04	157.07	157.06
Tre-s-92	8.60	8.80	7.87	9.23	8.47	8.96	8.36	**7.84**	8.38	7.86	7.89
Uta-s-92	3.50	3.80	**3.10**	3.94	3.52	3.65	3.50	**3.10**	3.40	**3.10**	3.13
Ute-s-92	25.30	27.70	25.94	27.57	25.86	26.89	25.80	25.32	25.80	25.33	**25.12**
Yor-f-83	36.40	39.60	36.18	40.94	38.72	39.34	36.68	36.06	36.53	36.12	**35.49**

- M1: ant algorithm (Eley 2006).
- M2: ant algorithm (Eley 2006).
- M3: Honey-bee Mating Optimization (Sabar, Ayob et al. 2009)
- M4: Hybrid Artificial Bee Colony Algorithm (Alzaqebah and Abdullah 2011)
- M5: Hybrid Particle Swarm Optimization (Ahandani, Baghmisheh et al. 2012)
- M6: artificial bee colony (Bolaji, Khader et al. 2012)
- M7: Global Best Artificial Bee Colony (Weng and Bin Asmuni 2013)
- M8: imperialist swarm-based optimization algorithm (Fong, Asmuni et al. 2014)
- M9: Hybrid Nature-Inspired Artificial Bee Colony Algorithm (Bolaji, Khader et al. 2015)
- M10: Hybrid Swarm Based Approach (Fong, Asmuni et al. 2015)
- M11: Hybrid bee colony optimization (Alzaqebah and Abdullah 2015)

Table (12) shows the results of different SI techniques implemented to solve the Curriculum-based course timetabling problem dataset taken from the ITC-2007. Ant colony optimization has shown better in comparison with other solutions used I literature.

Table (12) *results obtained from swarm intelligence techniques for solving the Curriculum-based course timetabling problem*

Instance	M1	M1	M2	M3	M4	M5
comp01	-	24	23	29	**5**	10
comp02	312	299	190	321	**86**	176
comp03	292	270	171	248	**101**	222
comp04	193	166	132	169	**57**	100
comp05	-	456	1483	822	**377**	606
comp06	336	255	237	275	**87**	178
comp07	324	253	259	279	**61**	123
comp08	218	173	154	185	**60**	112
comp09	302	271	190	282	**127**	172
comp10	274	239	210	246	**51**	125
comp11	293	220	18	251	**0**	1
comp12	-	751	583	752	**397**	622
comp13	-	214	156	213	**90**	136
comp14	236	221	165	219	**77**	141
comp15	284	238	193	286	**92**	189
comp16	281	236	215	255	**83**	155
comp17	331	280	206	300	**110**	148
comp18	196	173	122	173	**97**	132
comp19	304	276	205	252	**82**	156
comp20	372	241	263	284	**77**	147
comp21	-	364	233	352	**74**	246

- M1: improved Artificial Bee Colony (Bolaji, Khader et al. 2011)
- M2: improved Artificial Bee Colony (Junaedi and Maulidevi 2011)
- M3: Artificial Bee Colony Algorithm (Bolaji 2012)
- M4: Artificial Bee Colony Algorithm (MABC) (Agahian, Pehlivan et al. 2014)
- M5: Greedy Ants Colony Optimization (Kenekayoro and Zipamone 2016)

5. Discussion

In this section, the results of the systematic review are discussed. Moreover, future work directions have been drawn for further contribution and enhancement in the educational timetabling field. Therefore, in comparison with other previous reviews, studies and researchers opinion's the discussion focus on some hot topics, i.e. (Swarm intelligence techniques contribution to educational timetabling, and practice & theory in term of automated educational timetabling). This paper has used a systematic literature review method to investigate the use of swarm intelligence to solve the educational timetabling problem. The systematic review followed a precise protocol with respect to the number of swarm intelligence techniques used, which were: particle swarm optimization; Ant colony optimization; artificial bee colony; and firefly algorithm. These techniques were chosen for their wide usage in solving many optimization problems successfully as they are well-established techniques. Not forgetting the quite huge amount of research and literature dedicated only to enhance and develop them through complex hybridization and exploration. Alongside the fast growth of swarm intelligence techniques, some had not been fully implemented in complex problems such as the Firefly Algorithm (Yang 2010) and based on the review results firefly algorithm has a 0% percentage which means that this technique had never been implanted to solve educational timetabling problems (see figure 3) (see subsection 3.1.5)

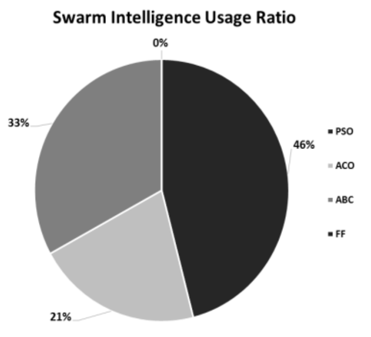

Figure 3

Although the field of swarm intelligence is growing fast day after another which helped in the development of this field. However, this kind of development only increased the number on available solutions without providing any general connection to these solutions. A scientific perspective rose saying that the amount of publications is increasing in a very fearful way that made it uneasy to find a generalized solution to the educational timetabling problem (Vrielink, Schepers et al. 2016) (Pillay 2012) (McCollum and Ireland 2006). A study by (Sörensen 2015) revealed that the striking rise of novel meta-heuristic methods did clearly turn the area of meta-heuristic away from scientific accuracy. Another study by (Weyland 2012) conducted in 2012 supported (Sörensen 2015) idea of how new metaphors can be misleading. Moreover, claiming that some metaphor is a novel technique based on scenarios inspired from natural phenomena such as flow of water or salmon run without scientifically proving the techniques worth with comparison with well-established techniques such as PSO, ACO etc. or rather analyzing how these techniques were developed. Based on the results of this paper, it is clear that some researchers focus on finding the optimal solution through novel techniques. Alongside, (Swan, Adriaensen et al. 2015) discussed the development of standard description of meta-heuristics in order to provide real scientific contribution to the field. This study agrees with (Sörensen 2015) and (Weyland 2012) in separating fancy metaphors inspired from nature or human. This standard is applied in order to create real practice in the field of meta-heuristic and by doing so increasing what is called transparency of implementation and understanding of contribution. “Mine’s better than yours” a study by (Paechter 2014) where it was highlighted that researchers Claims that particular algorithm or adaption to an algorithm out-performs the state of the art. (Paechter 2014) discussed that it is important to compare solutions in order to test the quality of the solution proposed in this paper it’s timetabling. Moreover, he underlined that it is important to work with the person using the timetable in reality to fully adjust the constraints of the problem and to understand the surroundings of the problem. It is also important to be careful that not all algorithms are good at solving a particular problem instances. (Paechter 2014) mentioned that over-fitting a particular algorithm just to solve a particular problem can provide research results but it is not helping in finding a general solution to the problem. During the research work, the authors did observe that the number of solutions to the educational timetabling problem has now become so large that it is difficult to generalize one solution to the whole problem. Consequently, the researchers considered the work of (Pillay 2016) in presenting an idea on generalizing the solutions for the educational timetabling problem although her idea is based on hyper-heuristics techniques. She proposed three levels of generality i.e. generalization over problem instances; generalization over problem-sets; and generalization over problem-type. (Pillay 2016) agreed with the authors and other researchers such as (Paechter 2014) on that a good solution’s performance in one type of problem instance does not necessarily mean it will perform well on other instances, on a different dataset, or other types of educational timetabling problems. Therefore, the idea presented by (Pillay 2016) helps in generalizing solutions to the educational timetabling problem. The researchers did however notice the difference between the vulnerability of each level’s types this includes, for example: the type of data used in experiments; the type of problem sets; and the way in which algorithms react differently to each problem type. Furthermore, an algorithm or a solution can react positively to one problem instance and negatively to another. It was clear from the literature collected that there is a distance between practice and theory in timetabling solutions. The use of datasets helped in testing the solutions provided by researchers but usually these solutions only work and inherit a specific instances and constraints, but if it’s used in different situations of educational timetabling problems they might provide low quality results. The distance discussed here is clear in timetable application in real world scenarios where optimization meta-heuristic techniques and researchers work is not implemented in real life for real testing and benefit of scientific contribution, or rather providing comparison between research work and real-world practice. Educational timetabling whether its university or school is a very complex and difficult task from both sides practice and theory. In a review by (Vrielink, Schepers et al. 2016) addressed practices in timetabling in higher education institutions. The review concluded that many research studies in the educational timetabling problem have been done and these have enhanced the solutions proposed to solve the problem. Additionally, the review analyzed state-of-the-art algorithms in the field that assist in providing an optimal solution; furthermore, the main contribution of the review was to lift the lid on the issues of variance and disharmony existing between theory and practice in higher education timetabling research. In addition, the review reported that the current literature lacks real world implementation of the timetabling optimization solutions. As the research work progressed the answers to the research questions stated in the introduction section became clear and at hand. The first and second questions were: What are the current swarm intelligence solutions for educational timetabling? and How to improve educational timetabling solutions through swarm intelligence techniques? From the above discussion, we can say that the enhancement in educational timetabling solutions can reach its prime through binding both theoretical and practical approaches. This is performed in order to test their validity and continue their development in a real-world environment where the problem instances can spread normally and the evaluation can have more realistic observations to it. Few studies in literature experimented the use of swarm intelligence in real-world timetabling such as the Greece studies (Tassopoulos and Beligiannis 2012, Tassopoulos and Beligiannis 2012) work in implementing PSO in high school timetable's in Greece which showed superior results to other researches in literature. This leads to the third question which was: How can real datasets contribute to providing better evaluation for educational timetabling solutions based on swarm intelligence algorithms? From the survey which was carried out, the use of real datasets did prove to be the best orientation for the researchers in the field of educational timetabling. Moreover, datasets like the international timetabling competition keep on providing new problem instances taken from real-world situations periodically. As the experiment data is being developed by experts in the field, the research work will continue in a path progressing towards better solutions. (McCollum and Ireland 2006) states that real world timetabling problems are too complicated to be solved and it is extremely hard to generate an applicable solution using constraints form a real world scenario. Based on this they explained why most researchers' uses more simplified problem which can be found in datasets benchmarks, it is due to the fact that datasets helps the research community to successfully develop new solutions and techniques in a much more simplified environment. Consequently, the Metaheuristics Network justified why it is better to use datasets when it comes to research point of view. First, because simple problems help in understanding how exactly the developed solutions or algorithm works with the problem constraints. Secondly, the complicity of real world data and its constraints make the research process long and hard. However, it is also important to notice that results gained from researchers in the field are quite irrelevant to real practice. So it's important to know how to overcome the issue of filling the gap between practice and theory and to investigate if actually utilizing different types of algorithms and techniques to fit a particular problem or a dataset is enough contribution to the field in matter of real industrial practice.

6. Conclusion

In summary, research in educational timetabling has been increasing rapidly in the last few years developing new competitive solutions. Optimization techniques such as swarm intelligence algorithms did contribute fairly to this research field. However, there are very successful swarm intelligence techniques have not yet been implemented. In this paper, we briefly reviewed the late state of the art findings in swarm intelligence utilization for educational timetabling problems. Complex problem such as educational timetabling require the use of benchmark datasets to help in simplifying the problem. However, it is important not to forget that real world scenarios differ in their features and constraints from research work. The gap between research and practice in educational timetabling has been recently a hot topic for timetabling research. More work is needed to fill this gab and this can set new research direction for future work.

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