SCITECH
RESEARCH ORGANISATION|

Volume 4, Issue 2
July 07, 2015|

Journal of Information Sciences and Computing Technologies
www.scitecresearch.com

Artificial Immune Algorithm for exams timetable

Tad Gonsalves and Rina Oishi
Department of Information and Communication Sciences,
Faculty of Science & Technology, Sophia University, Tokyo, Japan
t-gonsal@sophia.ac.jp, r-oishi@sophia.ac.jp

Abstract

The Artificial Immune System is a novel optimization algorithm designed after the resilient behavior of the immune system of vertebrates. In this paper, this algorithm is used to solve the constrained optimization problem of creating a university exam schedule and assigning students and examiners to each of the sessions. Penalties are imposed on the violation of the constraints. Abolition of the penalties on the hard constraints in the first stage leads to feasible solutions.In the second stage, the algorithm further refines the search in obtaining optimal solutions, where the exam schedule matches the preferences of the examiners.

Keywords: Artificial Immune System; clonal algorithm; optimization; constrained optimization; time-tabling problems.

1. Introduction

Timetabling is a subclass of scheduling problems where the task is to allocate events or activities to available slots in resources, subject to a set of constraints. Educational timetabling [1-3]mainly consists of the following categories: High School Timetabling, University Course Timetabling, and Examination Timetabling. High School timetabling problem essentially involves allocating class, teacher and room tuples to timetable slots so as to satisfy the hard and soft constraints[4]. In the University Course Timetabling, the time period is generally fixed as one lecture per week. The objective is to find a course schedule that is feasible with respect to a number of constraints[5].Examination Timetabling problems deal with assigning the examinations over an examination period subject to several constraints. The objective is to assign examinations to a minimum number of periods without any conflict[6].

Timetabling has been an active area of research for decades. It is a highly complex problem which involves the allocation of events (courses, teachers, and students) to a number of fixed resources (timeslots and rooms), satisfying many constraints. It is not possible to standardize the problem and formulate a general solution model owing tothe variations in educational and administrative policies, constraints and objectives across the institutions. Secondly, just like the general scheduling problem, the timetabling problem is shown to be NP hard [7-9].

Graph coloring methods, Integer Programming, Metaheursitic Algorithms, Hybrid Algorithms, etc. have been used to solve the complex timetabling problems with varying degrees of success. This study aims to solve a practical examination scheduling problem in the Department of Information and Communication Sciences, Sophia University, Tokyo. The problem is to schedule the final year under-grad students' thesis presentations, subject to a set of constraints imposed by the Department. It is a typical medium size problem involving 125 students and 30 examiners. There are four divisions in the Department. The principal examiner and the two assistant examiners are pre-assigned by the Department. The problem is scheduling the sessions taking into consideration, among other factors, the availability and the preferences of the staff.

So far, constructing the thesis presentation schedule has been a laborious and daunting task to the office staff at the end of each academic year. This study has made it possible to automate the scheduling task. It uses the AIS meta-heuristic algorithm for constructing an optimal schedule. Although the AIS is found to be successful in a wide variety of applications, researchers point out the potential of the algorithm as an *optimization tool* is not yet fully explored[10]. The contribution of this study is two-fold: (i) solving a real-life complex problem, and (ii) demonstrating that AIS is competent with the state-of the-art algorithms as an optimization tool.

The Artificial Immune System is an algorithm based on the immune system of the vertebrates [11-13]. The biological immune system is made up of primarily two types of cells - B cells which are produced in the bone marrow and T cells which are produced in the thymus. The pathogens like bacteria and viruses invading the body are called antigens. Both the antigen and the receptors on the surface of the B cells have three-dimensional structures. The affinity between the structure of the receptors and that of the antigen is a measure of the complementarities between the two. When an antigen invades the body, the immune system generates antibodies to diminish the antigen. Initially, the invaded antigen is recognized by a few of the B cells with high affinity for the antigen. Stimulated by the helper T cells, these high affinity B cells proliferate by cloning. This process is called clonal selection principle [14-15]. The new cloned cells undergo a high rate of somatic mutations called hyper-mutation. The mutations undergone by the clones are inversely proportional to their affinity to the antigen. The highest affinity antibodies experience the lowest mutation rates, whereas the lowest affinity antibodies have the highest mutation rates. The high affinity B cells and their clones proliferate and differentiate into plasma cells. Finally, the plasma cells generate a large number of antibodies to neutralize and eliminate the antigens.

After the cloning and hyper-mutation stage, the immune system must return to its normal condition, eliminating the extra cells. However, some cells remain circulating throughout the body as memory cells. When the immune system is later attacked by the same type of antigen (or a similar one), these memory cells are activated, presenting a better and more efficient secondary response.

This paper is organized as follows: Section 2 presents the literature review on the timetabling problem and the applications of the AIS algorithm. Section 3 presents the university exam schedule problem. Section 4 explains the major steps in the implementation of the Clonal Selection Algorithm for schedule optimization. Section 5 presents the results in a tabular form and section 6 concludes the study.

2. Literature Review

This section presents a literature review on the various strategies developed by researchers and institutions to solve the timetabling problems. In the second sub-section, literature review on the diverse applications of the Artificial Immune System is also presented.

2.1. Timetabling Problem Solution Strategies

Timetabling is an NP hard problem, just like the general scheduling problem. Moreover, the problem cannot be standardized and a general solution model devised owing to the variations in educational and administrative policies, constraints and objectives across the institutions. Following are some of the prominent solution strategies found in literature.

2.1.1 Graph Coloring Approach

The graph coloring problem, which has numerous applications in scheduling and other practical problems is one of the most studied NP-hard problems. Several variations of this problem are reported in the literature. For example, coloring the vertices of a graph such that no two adjacent vertices share the same color (vertex coloring); coloring the edges of a graph such that no two adjacent edges share the same color (edge coloring), and coloring the faces of planar graph such that no two faces that share a boundary have the same color (planar coloring) are some of the variations employed in solving practical problems [16]. In a typical graph coloring timetabling solution method, each node in the graph represents exams and the edge between the no desrepresents the conflict between these exams so that they cannot have the same color. Coloring an exam means scheduling it in a given period because each color representsa different time period [16-18].

2.1.2 Integer Programming

University course schedule and Exam time tables are represented as Integer Programming and Mixed Integer Programming problems and routinely solved using powerful solvers like CPLEX. In these techniques, the original time-tabling problem is divided into two or more sub-problems and solved sequentially in distinct stages. The divide and conquer approach reduces the computational time and yields better solutions[19-20].This approach is found to be scalable to medium and large size benchmark problems proposed by the International Timetabling Competitions [21].

2.1.3 Metaheuristic Algorithms

Meta-heuristic algorithms are domain independent since they do not rely on the domain knowledge to solve a problem.

They have been successfully applied to a wide range of problems. Simulated Annealing, a computational model based on the metallurgical metaphor is applied to solve the timetabling problem [22-23]. Evolutionary algorithms like the Genetic algorithm are also used in solving the timetabling problem [24-25]. Swarm Intelligence is another class of meta-heuristic algorithms based on the intelligent swarming behavior of social insects. The Ant Colony Optimization [26] and the Particle Swarm Optimization [27] belonging to the Swarm Intelligence paradigm, and a variety of hybrid algorithms are used extensively to solve the timetabling problem [28-31].

2.2. Artificial Immune Algorithm

Among the various mechanisms in the biological immune system that are explored, negative selection [32], immune network model [33] and clonal selection [34] are the most discussed models. The CLONALG algorithm based on the above clonal selection principle is also used in optimization. The following are the three main application areas of the AIS algorithm.

2.2.1 Machine Learning

Machine learning consists in constructing a functional model by extracting valuable features from a large data-set and then using it for prediction on unknown data sets. Supervised, unsupervised and reinforced learning are the most prominent categories of learning. AIS machine learning frameworks are found in [35-37].Modifications of AIS to handle pattern recognition and data mining are found in [38-42].

2.2.2 Anomaly detection

Anomaly detection is a widely researched problemin several application domains such as bio-informatics, health-care, fraud detection, and mechanical fault detection. Intrusion Detection (ID), being a particular case of Anomaly detection, detects intruders to an environmentby collecting and analyzing its behavior data. The self/non-self discrimination ability of the vertebrate immune systems which helps to distinguish between foreign objects and the body's own self forms the basis of the AIS anomaly detection mechanism. The negative selection algorithm makes use of a set of detectors to detect anomalies in input data. Das [43] describes two very successful negative selection algorithms for anomaly detection, and Yang provides a survey [44].

2.2.3 Optimization

De Castro presents an outline for tailoring the Clonal Selection Principle for handling numerical optimization problems [33][45-47]. It has been further extended to multi-modal optimization [48-49]. A rare case of the use of AIS for scheduling university course is found in [50].AIS by its nature is suited to pattern recognition and learning applications. Optimization applications of AIS found in literature are not too many. The principal objective of this paper is to demonstrate the efficiency of AIS as an optimization tool, for which a real-life exam timetabling problem is chosen as a target problem.

3. Exam Timetable

The Sophia University Information & Communication Sciences Department has four main divisions: Human-Machine (HUM), Communications (COM), Social (SOC), and Mathematics (MAT). The final-year students' thesis presentations exam requirements of the Human-Machine division are shown in Table 1. The other three divisions follow a similar schedule. The principal or the main examiner in each division should necessarily be assigned to the exam session of that particular division. The assistant examiners can be from the other divisions. The assignment of the examiners to a session is decided in advance by the Chair of the Department depending on their specializations. Each row in the table represents a presentation session. In each session, the duration of each presentation, the number of students, classroom, examiners and presentation priority are decided by the Department. Presentations with zero priority indicate the highest priority. They should be scheduled at the opening hour of the exam. Sessions with the same priority level can be interchangeably scheduled.

Table 1. Exam Sessions pre-determined by the Department

Presentation Time	Number of Students	Class-room	Main Examiner	Assistant Examiner 1	Assistant Examiner 2	Presentation Priority
25	6	Ichigaya-124	HUM - T1	HUM - T2	HUM - T3	0
25	3	Ichigaya-124	HUM - T2	HUM - T1	HUM - T3	0
15	3	Ichigaya-124	HUM - T3	HUM - T2	HUM - T1	0
25	4	Ichigaya-124	HUM - T4	HUM - T3	HUM - T2	0
25	5	Ichigaya-124	HUM - T5	COM - T1	HUM - T3	0
15	3	Ichigaya-124	HUM - T6	HUM - T5	HUM - T4	1
25	3	Ichigaya-124	HUM - T7	HUM - T6	COM - T6	1
25	3	Ichigaya-124	HUM - T8	HUM - T7	HUM - T9	2
25	5	Ichigaya-124	HUM - T9	HUM - T8	HUM - T7	0

The Information & Communication Sciences Department has elaborated a list of constraints that need to be satisfied in creating a feasible schedule. In this study, the constraints are divided into two categories – hard and soft constraints. Hard constraints ***must*** be satisfied to yield physically and temporally feasible solutions. Soft constraints, on the other hand, may at times be overlooked to yield sub-optimal solutions. The following sub-sections describe the two categories of constraints.

3.1 Hard Constraints

- An examiner cannot be assigned to more than one session at a given time.
- An examiner cannot be assigned to a time-slot when he/she is not available.
- The Yotsuya campus and the Ichigaya campus sessions must be at least 30 minutes apart.
- The priority assigned to the presentations by the Department must be strictly followed.

3.2 Soft Constraints

- An examiner may not be assigned to a time-slot he/she does not prefer.
- An examiner be assigned to multiple sessions contiguously.
- An examiner be assigned to consecutive exam days.
- The presentations be uniformly spread out throughout the exam days.

Table 2 shows the availability and preferences of the staff members. The symbol “X” implies that the staff member is not available during that particular time interval, while the symbol “Δ” implies that the staff member in question prefers not to be assigned to that particular time-slot. The former is a hard constraint, while the latter is a soft constraint. The Clonal Selection Algorithm optimizes the schedule by eliminating the hard as well as the soft constraints.

Table 2. Availability and preferencesof the Examiners

Date	Begin	End	COM - T1	COM - T2	COM - T3	COM - T4	COM - T5	COM - T6	COM - T7	COM - T8	COM - T9	COM - T10
2/12/2014	9:00	9:30			Δ				×			
2/12/2014	9:30	10:00			Δ				×			
2/12/2014	10:00	10:30							×			
2/12/2014	10:30	11:00							×			
2/12/2014	11:00	11:30							×			
2/12/2014	11:30	12:00							×			
2/12/2014	12:00	12:30							×			
2/12/2014	12:30	13:00							×			
2/12/2014	13:00	13:30							×			
2/12/2014	13:30	14:00	Δ						×			
2/12/2014	14:00	14:30							×			
2/12/2014	14:30	15:00							×			
2/12/2014	15:00	15:30							×			
2/12/2014	15:30	16:00							×			
2/12/2014	16:00	16:30							×			
2/12/2014	16:30	17:00							×			
2/12/2014	17:00	17:30							×			
2/12/2014	17:30	18:00			Δ				×			
2/13/2014	9:30	10:00			Δ							
2/13/2014	10:00	10:30			Δ							
2/13/2014	10:30	11:00										
2/13/2014	11:00	11:30										
2/13/2014	11:30	12:00										
2/13/2014	12:00	12:30										
2/13/2014	12:30	13:00										
2/13/2014	13:00	13:30										
2/13/2014	13:30	14:00										
2/13/2014	14:00	14:30										
2/13/2014	14:30	15:00										
2/13/2014	15:00	15:30										
2/13/2014	15:30	16:00										
2/13/2014	16:00	16:30										
2/13/2014	16:30	17:00										
2/13/2014	17:00	17:30										
2/13/2014	17:30	18:00										

4. Clonal Selection Algorithm for schedule optimization

The clonal selection algorithm is shown in Fig. 1. It consists of the following steps:

Generation of antibody population

A population consisting of N antibodies (Abs) is randomly generated. Each antibody represents a feasible solution to the optimization problem. The solution is a typical schedule, constructed without considering the constraints.

Objective function evaluation

The objective function is the sum of the penalties imposed on a given schedule for violating the hard and the soft constraints. Imposing penalties for the violation of constraints in optimization problems is arbitrary. The penalties in Table 3 show the relative importance of the constraints in the university exam schedule optimization. Penalties on the violation of the hard constraints are relatively higher than those on the violation of the soft constraints. The timetabling optimization problem is framed as a minimization problem and it seeks to optimize the schedule by minimizing the sum total of the penalties.

Affinity Calculation

The affinity (or the fitness) of each individual antibody is evaluated based on the value of the objective function mentioned above. The affinity is the reciprocal of the objective function.

Clone Selection

A certain percentage of the antibodies with greater affinities are selected from the population. These are then cloned to produce additional antibodies.

Affinity Proportional Mutation

The clones produced in the above step are subjected to mutations in proportion to their affinities.

Memory Renewal

The antibodies with relatively lower affinities (i.e., with higher values of the objective function) are eliminated. The selected clones are introduced into the antibody population as the immune memory cells. The above steps are iterated for M number of cycles. The antibody with the highest affinity (minimum values) found in all the iterations is the optimal solution.

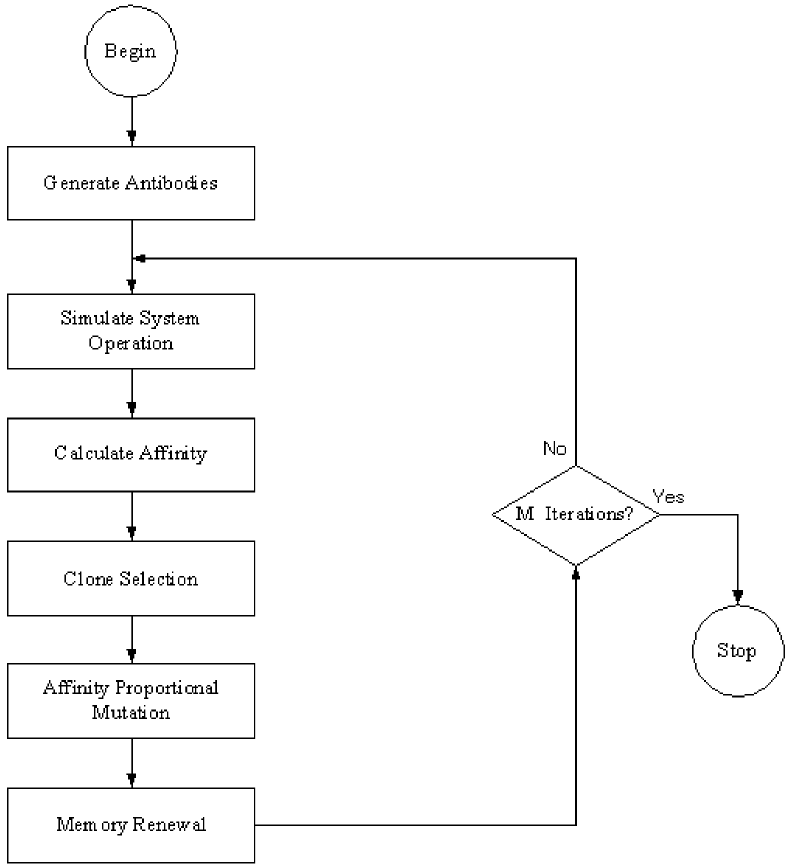

Fig 1: Clonal Selection Algorithm for exam schedule optimization

Table 3. Penalties imposed on the violated constraints

Contraints violated	Penalties imposed	
	Principal Examiner	**Assistant Examiners**
Hard Constraints		
1. Examiners are allocated to more than one session at the same time	500	500
2. Examiner unavailability (**X**) is not considered	500	500
3. Presentations shedule does not strictly follow the priorities in the list	500	
4. Yotsuya and Ichigaya campus sessions are not 30 minutes apart	400	
Soft Constraints		
1. Examiner preferences (△) are not considered	5	2
2. An examiner is not assigned to succesive sessions	10	8
3. An examiner is not assigned to successive exam days	50	45
4. Unequal student distribution on exam days	Twice the max difference between student numbers	

5. Simulation Results

Table 4. Optimized schedule for the Human-Machine division

HUMAN MACHINE INTERFACE DIVISION							
Date	Begin	End	Session time	Examiner 1	Examiner 2	Examiner 3	Students #
12-Feb-14	9:00	11:05	25	HUM - T5	COM - T1	HUM - T3	5
12-Feb-14	11:05	11:50	15	HUM - T6	HUM - T5	HUM - T4	3
12-Feb-14	12:50	15:20	25	HUM - T1	HUM - T2	HUM - T3	6
12-Feb-14	15:20	16:35	25	HUM - T7	HUM - T6	COM - T6	3
12-Feb-14	16:35	18:40	25	HUM - T9	HUM - T8	HUM - T7	5
13-Feb-14	9:00	10:40	25	HUM - T4	HUM - T3	HUM - T2	4
13-Feb-14	10:40	11:55	25	HUM - T8	HUM - T7	HUM - T9	3
13-Feb-14	12:55	14:10	25	HUM - T2	HUM - T1	HUM - T3	3
13-Feb-14	14:10	14:55	15	HUM - T3	HUM - T2	HUM - T1	3

Table 5. Optimized schedule for the Communications division

COMMUNICATIONS DIVISION							
Date	Begin	End	Session time	Examiner 1	Examiner 2	Examiner 3	Students #
2/12/2014	9:00	11:05	25	COM - T1	COM - T2	MAT - T3	5
2/12/2014	11:05	12:45	25	COM - T3	COM - T2	COM - T1	4
2/12/2014	13:45	15:00	25	COM - T4	SCO - T3	COM - T2	3
2/12/2014	15:00	17:05	25	COM - T2	COM - T1	COM - T3	5
2/13/2014	9:30	11:10	25	COM - T7	COM - T6	COM - T5	4
2/13/2014	11:10	13:40	25	COM - T6	COM - T5	COM - T4	6
2/13/2014	14:40	16:45	25	COM - T5	COM - T1	COM - T3	5

Table 6. Optimized schedule for the Social division

SOCIAL DIVISION							
Date	Begin	End	Session time	Examiner 1	Examiner 2	Examiner 3	Students #
2/12/2014	9:30	11:10	20	SCO - T5	SCO - T1	SCO - T7	5
2/12/2014	11:10	13:10	20	SCO - T7	SCO - T6	COM - T6	6
2/12/2014	14:10	15:50	20	SCO - T6	SCO - T5	SCO - T4	5
2/12/2014	15:50	17:50	20	SCO - T1	HUM - T2	SCO - T3	6
2/13/2014	9:30	11:10	20	SCO - T4	SCO - T3	SCO - T2	5
2/13/2014	11:10	12:50	20	SCO - T3	SCO - T2	SCO - T1	5
2/13/2014	13:50	15:10	20	SCO - T2	SCO - T1	SCO - T3	4

Table 7. Optimized schedule for the Math division

MATH DIVISION							
Date	Begin	End	Session time	Examiner 1	Examiner 2	Examiner 3	Students #
2/12/2014	10:00	10:45	15	MAT - T10	MAT - T9	MAT - T8	3
2/12/2014	10:45	11:30	15	MAT - T12	MAT - T11	MAT - T10	3
2/12/2014	11:30	12:15	15	MAT - T9	MAT - T8	MAT - T7	3
2/12/2014	13:15	14:00	15	MAT - T7	MAT - T6	MAT - T5	3
2/12/2014	14:00	14:45	15	MAT - T6	MAT - T5	MAT - T4	3
2/12/2014	14:45	15:30	15	MAT - T5	MAT - T1	MAT - T3	3
2/12/2014	15:30	16:15	15	MAT - T8	MAT - T7	MAT - T6	3
2/13/2014	10:00	10:45	15	MAT - T4	MAT - T3	MAT - T2	3
2/13/2014	10:45	11:30	15	MAT - T3	MAT - T2	MAT - T1	3
2/13/2014	11:30	12:45	15	MAT - T2	MAT - T1	MAT - T3	5
2/13/2014	13:45	14:30	15	MAT - T1	MAT - T2	MAT - T3	3
2/13/2014	14:30	15:15	15	MAT - T11	MAT - T10	MAT - T9	3

Tables 1, 2, 3, and 4 show the optimized schedules produced by the optimization algorithm for the Human-Machine, Communications, Social and the Math divisions, respectively. The schedule for the Communications division is ***optimal***, satisfying all the hard as well as the soft constraints imposed by the Department. However, the schedules for the rest of the three divisions are sub-optimal. The soft constrains that cannot be eliminated are shown as purple colored slots. For example, in the Human-Machine division, the assignment of Professor “HUM-T3” as Assistant Examiner is not according to his/her preference. Similar is the case of Professor “SCO-T1” in the Social division, and Professor “MAT-T1” in the Math division. This is because of the highly complex nature of the heavily constrained optimization problem. However, this is not a “should be avoided by all means” hard and fixed constraint, and, therefore, the schedule is feasible. Secondly, there is just one soft constraint that is being violated in the schedules of each of these three division. Therefore, although sub-optimal, each of these three schedules are next in rank to the optimal solution and are approved by the Department office.

The performance of the algorithm in a sample run is shown in Table 8. The algorithm works with no more than 10 antibodies so as to avoid long computational time. In this particular scenario, the initial total penalty is 6465. After the completion of stage 1 (i.e. obtaining solutions that do not violate the hard constraints), the penalty is reduced to 3149. With about 40 mutations in the generation cycles, stage 1 is completed in about 56 seconds. The second stage calculations are iterated about a 100 times. The total penalty reduces to 1633 and the computation time is about 120 seconds. Stage 2 generations may be further iterated to reduce the penalties on soft constrains till a desired optimal schedule is obtained. The Department office found the above performance results satisfactory and finalized the exam schedule.

Table 8. Clonal Selection Algorithm performance parameters

Population of antibodies	10
Total penalty on the initial solution	6465
Number of mutations in stage 1	40
Computation time for stage 1	56 seconds
Penalty after completing stage 1	3149
Computation time for stage 2 (100 iterations)	120 seconds
Penalty after completing stage 2	2633

6. Conclusion

The Artificial Immune System is a novel optimization algorithm designed after the resilient behavior of the immune system of vertebrates. The algorithm by its very nature is suited to solve problems in pattern recognition, machine learning, data mining and anomaly detection. Although some versions of the AIS algorithm, such as the ones based on the clonal selection principle, have been successfully applied to the optimization problems, some researchers hold that the algorithm has not been fully tested as a competent optimization strategy. The aim of this paper is to demonstrate the capability of AIS in optimizing a real-life complex timetabling problem. The problem introduced in this paper in the scheduling of final-year presentations exam sessions in the Department of Information and Communication Sciences, Sophia University, Tokyo. It consists of hard constraints such as the availability of classrooms, time-slots and examiners, etc., as well as soft constraints, such as the preferences of the examiners, etc. The AIS algorithm solves the problem in two stages. In stage one it constructs feasible solutions that do not violate the hard constraints. In stage two, it refines the stage-one solutions to successfully accommodate the soft constraints.

References

[1] Burke, E.K., Newall.J.P. (1999). A multistage evolutionary algorithm for the timetable problem. *IEEE Transactions on Evolutionary Computation*, 3 (1):63-74.

[2] Melício, F., Caldeira, P., Rosa, A. (2005). Solving real school timetabling problems with meta-heuristics. *Proceedings of the 4th WSEAS International Conference on Applied Mathematics and Computer Science*, 4, pp.14-8.

[3] Simon Kristiansen, Matias Sørensen, and Thomas R. Stidsen. (2011). Elective course planning. European Journal of Operational Research, 215(3):713-720.

[4] Nelishia Pillay. (2014). A survey of school timetabling research. *Annals of Operations Research*, Springer, 218(1): 261-293.

[5] McCollum.B. (2006). University timetabling: Bridging the gap between research and practice. *Proceedings of the 5th International Conference on the Practice and Theory of Automated Timetabling*, pp.15-35. Springer.

[6] Qu,R.,Burke,E.K.,McCollum, B., Merlot, L.T.G.,Lee,S.Y. (2009).A survey of search methodologies and automated system development for examination timetabling. *Journal of Scheduling*, 12(1):55-89.

[7] Even, S., Itai, A., Shamir, A. (1976).On the complexity of timetable and multicommodity flow problems. *SIAM Journal on Computing*, 5, pp. 691-703.

[8] de Werra, D. The combinatorics of timetabling. European Journal of Operational Research, 96, 504–513, 1997.

[9] Eikelder H.M., Willemen, R.J.(2001).Some complexity aspects of secondary school timetabling problems. Computer Science Practice and Theory of Automated Timetabling III. *Lecture Notes in Computer Science*, 2079, pp. 18-27.

[10] Emma Hart, Jon Timmis. (2008). Application areas of AIS: The past, the present and the future.*Applied Soft Computing, 8*, pp. 191-201.

[11] de Castro L.N., Von Zuben, F.J. (2000). Artificial immune systems: Part II—A survey of application. State Univ. Campinas, Campinas, Brazil, Tech. Rep. RT DCA 02/0065.

[12] de Castro, L.N., Timmis, J. (2002). *Artificial Immune Systems: A New Computational Intelligence Approach*. Springer-Verlag, London.

[13] Timmis, J., Knight, T., de Castro L.N., Hart, E. (2004). An Overview of artificial immune systems. Computation in Cells andTissues: Perspectives and Tools Thought. *Natural Computation Series*. Springer-Verlag.pp.51-86.

[14] Ada, G.L., Nossal, G. (1987). The Clonal Selection Theory. *Scientific American*. 257(2): 50-57.

[15] Dasgupta, D. (2006). Advances in artificial immune systems. *IEEE Comput. Intell. Mag.*1(4): 40-4.

[16] Cauvery, N. K.(2011). Timetable Scheduling using Graph Coloring, International Journal of P2P Network Trends and Technology- 1(2):57-62.

[17] Burke, E. K., Elliman, D. G., and Weare, R. (1993). A university timetabling system based on graph coloring and constraintmanipulation.*Journal of Research on Computing in Education*, 26.

[18] Akbulut, A. and Yılmaz, G.(2013). University Exam Scheduling System Using Graph Coloring Algorithm and RFID Technology.*International Journal of Innovation, Management and Technology*, 4(1): 66-72.

[19] MirHassani, S.A. (2006). A computational approach to enhancing course timetabling with integer programming.*Applied Mathematics and Computation*, 175(1): 814-822.

[20] Daskalaki, S.,Birbas, T.(2005). Efficient solutions for a university timetabling problem through integer programming.*European Journal of Operational Research*. 160(1): 106-120.

[21] Phillips, A.E., Waterer, H., Ehrgott, M., Ryan, D.M. (2015). Integer programming methods for large-scale practical classroom assignment problems. *Computers & Operations Research*, Volume 53, pp. 42-53.

[22] Thompson, J. Dowsland, K. (1998). A robust simulated annealing based examination timetabling system, *Computers and Operations Research*, vol. 25, pp. 637-648.

[23] Chainate, W.,Thapatsuwan, P.,Pongcharoen, P. (2008). Investigation on Cooling Schemes and Parameters of Simulated Annealing for Timetabling University Courses.*International Conference on Advanced Computer Theory and Engineering, ICACTE '08*.pp.200-204.

[24] N. Pillay, W. Banzhaf, An informed genetic algorithm for the examination timetabling problem, *Applied Soft Computing*. 10(2):457-467.

[25] Cuupic, M., Golub, M.,Jakobovic, D. Exam timetabling using genetic algorithm. (2009).*Proceedings of the 31st ITI International Conference on Information Technology Interfaces, ITI '09*. pp. 357-362.

[26] Nothegger, C., Mayer, A.,Chwatal, A., Raidl, G. (2012). Solving the post enrolment course timetabling problem by ant colony optimisation. *Ann. Oper. Res.*194, pp.325-339.

[27] Qarouni-Fard, D.,Najafi-Ardabili, A.,Moeinzadeh, M.-H.(2007). Finding Feasible Timetables with Particle Swarm Optimization,*4th International Conference on Innovations in Information Technology, IIT '07*. pp. 387-391.

[28] Shiau, D.F. (2011). A hybrid particle swarm optimization for a university course scheduling problem with flexible preferences. *Expert Syst. Appl., 38*, pp. 235-248.

[29] Ho, I.S.F.,Safaai, D., Zaiton, M. (2009). A Combination of PSO and Local Search in University Course Timetabling Problem. *International Conference on Computer Engineering and Technology, ICCET '09*. Volume: 2.

[30] Ayob, M., Jaradat, G.(2009). Hybrid Ant Colony systems for course timetabling problems.*2nd Conference on Data Mining and Optimization, DMO '09*. pp. 120-126.

[31] Badoni, R.P.,Gupta,D.K., Mishra, P.(2014). A new hybrid algorithm for university course timetabling problem using events based on groupings of students. *Computers & Industrial Engineering*, Volume 78, pp. 12-25.

[32] Timmis, J., Neal, M., Knight, T.(2002). AINE: Machine Learning Inspired by the Immune System. *IEEE Transactions on Evolutionary Computation.*

[33] de Castro L.N., Timmis, J.(2002). An artificial immune network for multimodal function optimization. In: *Proc. IEEE Congress on Evolutionary Computation*, vol. 1, pp. 699-674.

[34] de Castro L.N., Von Zuben, F.J.(2002). Learning and optimization using the clonal selection principle. *IEEE Trans. Evol. Comput.* 6(3): 239-251.

[35] Glickman, M.,Balthrop, J. Forrest, S.(2005). A Machine Learning Evaluation of an Artificial Immune System, *Evolutionary Computation*.13(2):179-212.

[36] Hofmeyr, S; Forrest, S. (2000). Architecture for an Artificial Immune System, *Evolutionary Computation*.8(4): 443-473.

[37] Nasraoui, O., Rojas, C., Cardona, C. (2006). A framework for mining evolving trends in web data streams using dynamic learning and retrospective validation, *Comput. Networks 50*. pp. 1425-1429.

[38] Deng, J., Jiang, Y., Mao, Z.(2007). An Artificial Immune Network Approach for Pattern Recognition, *Third International Conference on Natural Computation, ICNC 2007*.Haikou.vol. 3, pp. 635-640,

[39] de Castro L.N., Von Zuben, F.J.(2001).aiNet: An artificial immune network for data analysis. In: *Data Mining: A Heuristic Approach*, H.A. Abbass, R.A. Sarker, and C.S. Newton (eds). Idea Group Publishing, USA, pp. 231-259.

[40] de Castro L.N., Von Zuben, F.J.(2002). Learning and optimization using the clonal selection principle. *IEEE Trans. Evol. Comput.* 6(3):239-251.

[41] Timmis, J., Neal, M., Hunt, J. E. (2000). An artificial immune system for data analysis. *Biosystem*. 55(1/3):143-150.

[42] Timmis, J., Neal, M., Knight, T. (2002). AINE: Machine Learning Inspired by the Immune System. *IEEE Transactions on Evolutionary Computation*.

[43] Das, S., Gui, M., Pahwa, A. (2008). Artificial Immune Systems for Self-Nonself Discrimination: Application to Anomaly Detection. *Advances of Computational Intelligence in Industrial Systems Studies in Computational Intelligence*. Volume 116,pp. 231-248.

[44] Yang, H., Li, T., Hu, X., Wang, F., Zou, Y. (2014). A Survey of Artificial Immune System Based Intrusion Detection. *The Scientific World Journal*. Volume 2014, Article ID 156790, 11 pages. http://dx.doi.org/10.1155/2014/156790

[45] Gonsalves, T. (2012). CLONALG for improving software development cost models.*Advances in Computer Science & Engineering*. 9(2):133-151.

[46] Zhang, W. Yen, G.G., He, Z. (2014). Constrained Optimization Via Artificial Immune System, *IEEE Transactions onCybernetics.* 44(2):185-198.

[47] de Mello, H. L.,Leite da Silva, A.M.; Barbosa, D.A. (2012). A Cluster and Gradient-Based Artificial Immune System Applied in Optimization Scenarios, *IEEE Transactions on Evolutionary Computation*.16(3): 301-318.

[48] de Castro L.N., Timmis, J. (2002). An artificial immune network for multimodal function optimization. In*: Proc. IEEE Congress on Evolutionary Computation*, vol. 1, pp. 699-674.

[49] Gonsalves, T. Aiso, Y. (2012). Multi-modal Optimization using a Simple Artificial Immune Algorithm, *ICCGI2012*.

[50] Malim, M.R.,Khader, A.T., Mustafa, A. (2006).An immune-based approach to university course timetabling: Immune network algorithm. *International Conference on Computing & Informatics*, *ICOCI '06*, pp. 1 – 6.