# A syllabus on bio-inspired computing with student outcomes evaluation

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***Abstract*—Bio-inspired algorithms is an important approach in computer science which are based on the principles of the biological evolution and animal or insect behavior. We have considered twelve of the most know bio-inspired algorithms for proposed a syllabus for undergraduate course in a computer science program. The main objective of this paper is to detail the student outcomes evaluation based on accreditation criteria for computer programs proposed by the Institute for Quality and Accreditation of Computer, Engineering and Technology Programs (ICACIT) in 2019. Furthermore, we shows the analysis and results of the student outcomes evaluation in a course of the Computer Science Program of the National University of San Agustin of Arequipa (UNSA) where we obtain over 80% between excellent and satisfactory from five of the eight performance indicators evaluated.**

***Index Terms*—Bio-inspired algorithms, syllabus, student outcomes, ICACIT**

## I. Introduction

Bio-inspired computing is a field of study that explores various computational methods that draw inspiration from biology. These methods facilitate the creation of novel problem-solving tools and are often grounded in natural patterns, the behaviors of living organisms, and even the structural characteristics of organisms themselves [1].

Currently, bio-inspired algorithms have been widely used in a several domains, including security, electronics image processing, computer networks, robotics, mechanical problems, electrical, production engineering, management, planetary, among others [2].

In the proposed syllabus, we consider twelve of the most well-known bio-inspired algorithms:

1) genetic algorithms [3],
2) memetic algorithms [4],
3) multi-objective genetic algorithm [5],
4) genetic programming [6],
5) evolution strategies [7],
6) evolutionary programming [8],
7) differential evolution [9],
8) ant colony optimization [10],
9) particle swarm optimization [11],
10) artificial bee colony [12],
11) clonal selection algorithm [13], and
12) negative selection algorithm [14].



The previous algorithms can be grouped into three sub-fields of artificial intelligence, the first seven algorithms belong to Evolutionary Algorithms, the next three algorithms belong to Swarm Intelligence or Social Computing, and, the last two algorithms belong to Inmunocomputing or Artificial Immune Systems [15].

The main objective of this paper is to define performance indicators and rubric in an assessment of student outcomes for ICACIT accreditation based on the bio-inspired algorithms mentioned. We consider four of the ten student outcomes proposed by ICACIT in 2021 for computing programs and computer science programs. The student outcomes evaluation was held in a course of the computer science program (accredited by ICACIT from 2018 to 2025) at UNSA.

The paper is structured as follows: Section 2 presents the syllabus proposed and shows the learning objectives, student outcomes, performance indicators, and rubrics considered. Section 3 shows the results obtained from the student outcomes evaluation. Finally, in Section 4, the conclusions are drawn and some future works are proposed.

## II. The Proposed Syllabus

The proposed syllabus is divided into three modules:

1) Evolutionary algorithms.
2) Swarm intelligence algorithms.
3) Artificial immune system algorithms.

### A. Topics

The evolutionary algorithms module is divided into seven topics (each topic has a laboratory):

- Topic 1: Genetic Algorithms (Laboratory 1: To implement a genetic algorithm).
- Topic 2: Memetic Algorithms (Laboratory 2: To implement a memetic algorithm).
- Topic 3: Multi-Objective Genetic Algorithm (Laboratory 3: To implement a multi-objective genetic algorithm).
- Topic 4: Genetic Programming (Laboratory 4: To implement a genetic programming algorithm).
- Topic 5: Evolution Strategies (Laboratory 5: To implement an evolutionary strategy algorithm).
- Topic 6: Evolutionary Programming (Laboratory 6: To implement an evolutionary programming algorithm).

- Topic 7: Differential Evolution (Laboratory 7: To implement a differential evolution algorithm).

The swarm intelligence module is divided into three topics (each topic has a laboratory):

- Topic 8: Ant Colony Optimization (Laboratory 8: To implement an ant colony optimization algorithm).
- Topic 9: Particle Swarm Optimization (Laboratory 9: To implement a particle swarm optimization algorithm).
- Topic 10: Artificial Bee Colony (Laboratory 10: To implement an artificial bee colony algorithm).

The artificial immune system module is divided into two topics (each topic has a laboratory):

- Topic 11: Clonal Selection Algorithm (Laboratory 11: To implement a clonal selection algorithm).
- Topic 12: Negative Selection Algorithm (Laboratory 12: To implement a negative selection algorithm).

### B. Student Outcomes

For the student outcomes evaluation, we analyze four student outcomes considered in the accreditation criteria for computer programs proposed by ICACIT in 2019:

- Computer Knowledge ($a$): The ability to apply knowledge of mathematics, science, computers, and a computer specialty appropriate to student outcomes and program discipline (Level 2: Apply at intermediate level).
- Design and Development of Solutions ($c$): The ability to design, implement, and evaluate solutions to complex computing problems and to design and evaluate systems, components, or processes that meet specific needs (Level 2: Apply at the intermediate level).
- Individual and Team Work ($d$): The ability to function effectively as an individual, as a member or leader of diverse teams. (Level 2: Comprises).
- Communication ($e$): The ability to communicate effectively, orally and in writing, in a variety of professional contexts. (Level 2: Comprises).

### C. Performance Indicators and Rubrics

Two performance indicators for student outcomes $a$ are defined: $a1$ and $a2$. The performance indicators and rubrics for each one are detailed below.

$a1$ Demonstrates knowledge of Algorithms within the Branch of Evolutionary Computing.

1) Unsatisfactory: Does not demonstrate knowledge of the Algorithms within the Branch of Evolutionary Computing seen in the course.
2) Partially Satisfactory: Demonstrates knowledge of less than 30% of the Algorithms within the Branch of Evolutionary Computing seen in the course.
3) Satisfactory: Demonstrates knowledge of more than 30% and less than 80% of the Algorithms within the Branch of Evolutionary Computing seen in the course.
4) Excellent: Demonstrates knowledge of more than 80% of the Algorithms within the Branch of Evolutionary Computing seen in the course.

$a2$ Demonstrates knowledge of Algorithms within the Social Computing Branch.

1) Unsatisfactory: Does not demonstrate knowledge of the Algorithms within the Social Computing Branch seen in the course.
2) Partially Satisfactory: Demonstrates knowledge of less than 30% of the Algorithms within the Social Computing Branch seen in the course.
3) Satisfactory: Demonstrates knowledge of more than 30% and less than 80% of the Algorithms within the Evolutionary Social Branch seen in the course.
4) Excellent: Demonstrates knowledge of more than 80% of the Algorithms within the Social Computing Branch seen in the course.

Two performance indicators for student outcomes $c$ are defined: $c1$ and $c2$. The performance indicators and rubrics for each one are detailed below.

$c1$ Solves problems with implemented algorithms within the Branch of Evolutionary Computing.

1) Unsatisfactory: It does not solve problems implementing the Algorithms within the Branch of Evolutionary Computing seen in the course.
2) Partially Satisfactory: Solves problems implementing less than 30% of the Algorithms within the Branch of Evolutionary Computing seen in the course.
3) Satisfactory: Solves problems implementing more than 30% and less than 80% of the Algorithms within the Branch of Evolutionary Computing seen in the course.
4) Excellent: Solves problems implementing more than 80% of the Algorithms within the Branch of Evolutionary Computing seen in the course.

$c2$ Solves problems with implemented algorithms within the Social Computing Branch.

1) Unsatisfactory: Does not solve problems implementing the Algorithms within the Social Computing Strand in the course.
2) Partially Satisfactory: Solves problems implementing less than 30% of the Algorithms within the Social Computing Branch seen in the course.
3) Satisfactory: Solve problems implementing more than 30% and less than 80% of the Algorithms within the Social Computing Branch seen in the course.
4) Excellent: Solves problems implementing more than 80% of the Algorithms within the Social Computing Branch seen in the course.

Two performance indicators for student outcomes $d$ are defined: $d1$ and $d2$. The performance indicators and rubrics for each one are detailed below.

$d1$ Performs the implementation of a Bio-inspired Algorithm not studied in the Course.

1) Unsatisfactory: Does not implement a Bio-inspired Algorithm.

2) Partially Satisfactory: Performs with errors the implementation of a Bio-inspired Algorithm.
3) Satisfactory: Implementation of a Bio-inspired Algorithm without errors.
4) Excellent: Performs the implementation of a Bio-inspired Algorithm without errors and optimizes its performance.

$d2$ Shows examples of solving complex problems using a Bio-inspired Algorithm not studied in the Course.

1) Unsatisfactory: Does not show examples of solving complex problems using a Bio-inspired Algorithm.
2) Partially Satisfactory: Shows an example of solving complex problems using a Bio-inspired Algorithm.
3) Satisfactory: Shows two examples of solving complex problems using a Bio-inspired Algorithm.
4) Excellent: Show three or more examples of solving complex problems using a Bio-inspired Algorithm.

Two performance indicators for student outcomes $e$ are defined: $e1$ and $e2$. The performance indicators and rubrics for each one are detailed below.

$e1$ Makes the exhibition of the Final Work.

1) Unsatisfactory: Do not present the final Work.
2) Partially Satisfactory: Present the final work without preparation.
3) Satisfactory: Present the final work with preparation.
4) Excellent: Present the final work with preparation and in detail.

$e2$ Make a video explaining the Final Work.

1) Unsatisfactory: Do not make the explanation video for the Final Project.
2) Partially Satisfactory: Make the explanation video of the Final Project without preparation.
3) Satisfactory: Make the explanation video of the Final Project with preparation.
4) Excellent: Make the explanation video of the Final Project with preparation and in detail.

## III. The Evaluation

The student outcomes evaluation defined in the previous section was held with sixteen students in the bio-inspired computing course of Computer Science Program at the UNSA in the first Semester of the 2021 academic year.

The performance indicator $a1$ and $a2$ were evaluated based on the first exam (week 7) and the second exam (week 12) respectively. Table I, Figure 1 and Figure 2 show the results obtained.

The performance indicator $c1$ and $c2$ were evaluated based on laboratories 1, 2, 3, 4, 5, 6 , 7 (week 1 to 7) and laboratories 8, 9, 10, 11, 12 (week 8 to 12) respectively. Table II, Figure 3 and Figure 4 show the results obtained.

The performance indicator $d1$ and $d2$ were evaluated based on the final project (week 17). Table III, Figure 5 and Figure 6 show the results obtained.

The performance indicators $e1$ and $e2$ were evaluated based on the final project (week 17). Table IV, Figure 7 and Figure 8 show the results obtained.

TABLE I
ACHIEVEMENT LEVEL FOR EACH STUDENT IN THE STUDENT OUTCOME $a$

| Student | a1 | a2 |
|---|---|---|
| 1 | 3 | 4 |
| 2 | 3 | 3 |
| 3 | 3 | 3 |
| 4 | 2 | 1 |
| 5 | 3 | 3 |
| 6 | 3 | 4 |
| 7 | 3 | 3 |
| 8 | 3 | 3 |
| 9 | 3 | 2 |
| 10 | 3 | 4 |
| 11 | 1 | 1 |
| 12 | 3 | 4 |
| 13 | 3 | 1 |
| 14 | 3 | 3 |
| 15 | 3 | 4 |
| 16 | 3 | 3 |

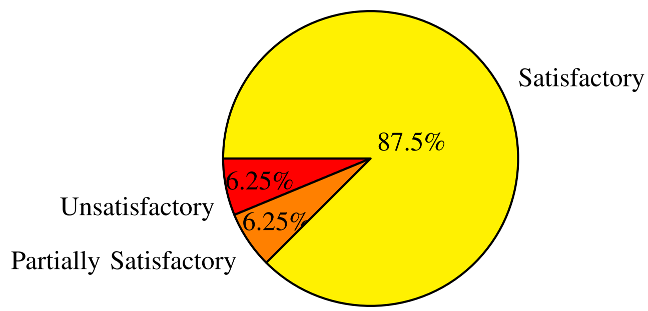


Fig. 1. Summary of Student Outcome Levels of Achievement $a1$

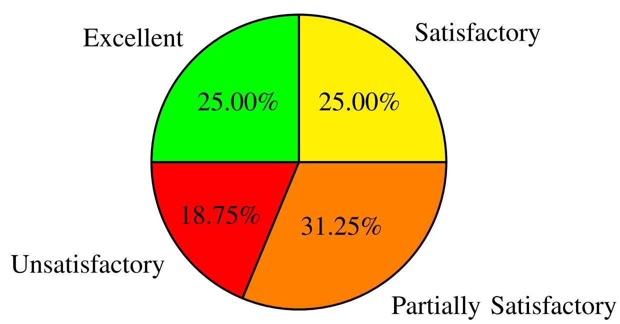


Fig. 2. Summary of Student Outcome Levels of Achievement $a2$

TABLE II
LEVEL OF ACHIEVEMENT FOR EACH STUDENT IN THE STUDENT OUTCOME [C]

| Student | c1 | c2 |
|---|---|---|
| 1 | 4 | 4 |
| 2 | 3 | 3 |
| 3 | 2 | 3 |
| 4 | 3 | 2 |
| 5 | 4 | 4 |
| 6 | 4 | 4 |
| 7 | 4 | 4 |
| 8 | 4 | 4 |
| 9 | 4 | 4 |
| 10 | 3 | 4 |
| 11 | 2 | 1 |
| 12 | 4 | 4 |
| 13 | 3 | 4 |
| 14 | 3 | 4 |
| 15 | 4 | 4 |
| 16 | 4 | 4 |

TABLE III
ACHIEVEMENT LEVEL FOR EACH STUDENT IN STUDENT OUTCOME $d$

| Student | d1 | d2 |
|---|---|---|
| 1 | 4 | 2 |
| 2 | 4 | 2 |
| 3 | 3 | 2 |
| 4 | 1 | 1 |
| 5 | 4 | 4 |
| 6 | 4 | 3 |
| 7 | 2 | 2 |
| 8 | 3 | 2 |
| 9 | 3 | 2 |
| 10 | 4 | 3 |
| 11 | 2 | 2 |
| 12 | 4 | 3 |
| 13 | 4 | 4 |
| 14 | 3 | 3 |
| 15 | 3 | 3 |
| 16 | 3 | 4 |

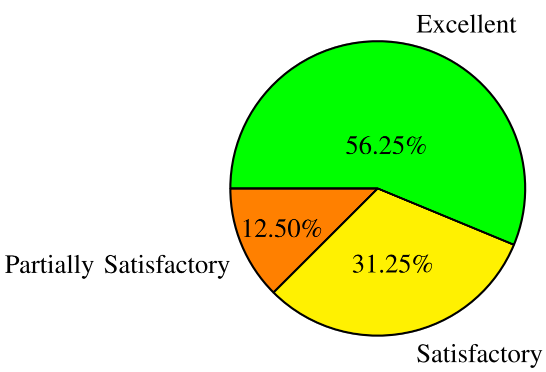


Fig. 3. Summary of Student Outcome Levels of Achievement $c1$

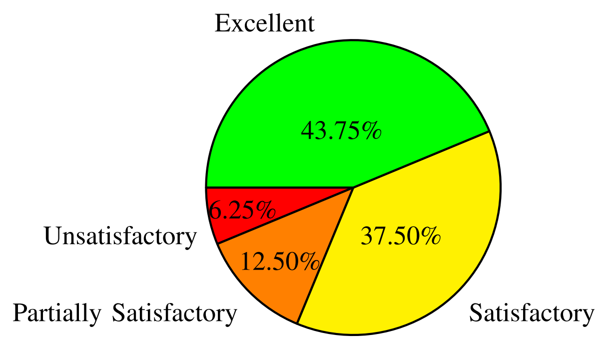


Fig. 5. Summary of Student Outcome Levels of Achievement $d1$

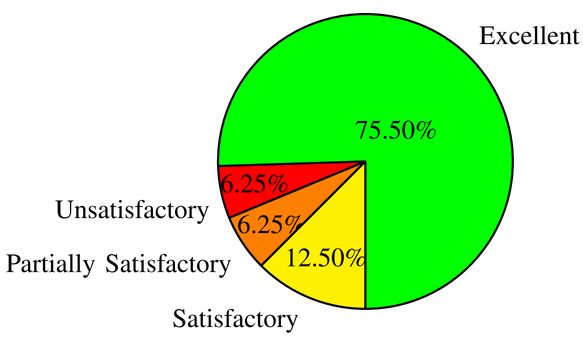


Fig. 4. Summary of Student Outcome Levels of Achievement $c2$

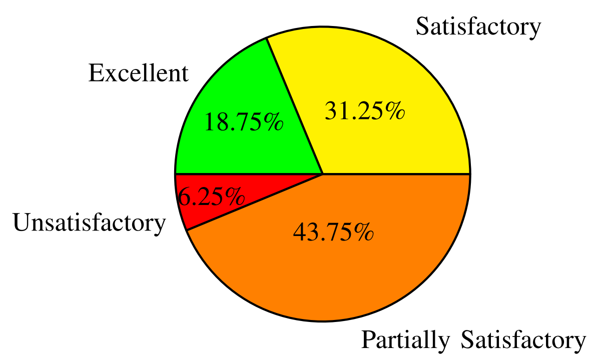


Fig. 6. Summary of Achievement Levels in Student Outcome $d2$

TABLE IV
LEVEL OF ACHIEVEMENT FOR EACH STUDENT IN STUDENT OUTCOME $e$

| Student | e1 | e2 |
|---|---|---|
| 1 | 3 | 4 |
| 2 | 3 | 2 |
| 3 | 2 | 3 |
| 4 | 2 | 2 |
| 5 | 3 | 3 |
| 6 | 2 | 3 |
| 7 | 3 | 3 |
| 8 | 3 | 3 |
| 9 | 3 | 2 |
| 10 | 3 | 4 |
| 11 | 3 | 2 |
| 12 | 3 | 2 |
| 13 | 3 | 2 |
| 14 | 3 | 2 |
| 15 | 3 | 2 |
| 16 | 3 | 4 |

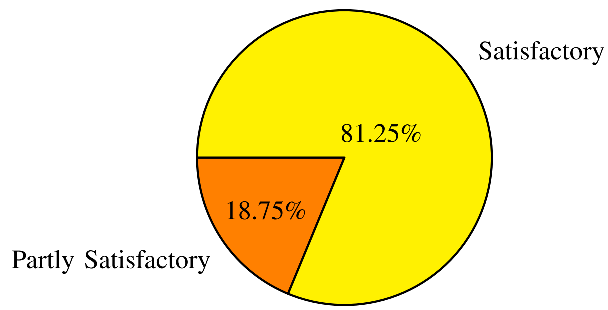


Fig. 7. Summary of Achievement Levels in Student Outcome $e1$

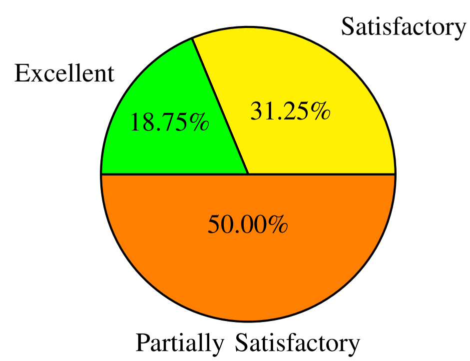


Fig. 8. Summary of Achievement Levels in Student Outcome $e2$

Finally, Table V shows a summary of the results achieved where we obtain over 80% between excellent and satisfactory from five of the eight performance indicators evaluated.

## IV. CONCLUSIONS

In this paper, we propose a syllabus for a bio-inspired computing course and present the parts, topics, assignments, and learning objectives. Furthermore, we detail the performance indicators and rubrics for the student outcomes evaluation based on the accreditation criteria for computer programs proposed by ICACIT in 2019. Finally, we show the results of the student outcomes evaluation in a bio-inspired computing course of the computer science program at UNSA (the program is accredited by ICACIT from 2019 to 2025).

We anticipate several potential directions for future endeavors, including: 1) adapting the performance indicators and rubrics to students outcomes in the accreditation criteria for computer programs proposed by ICACIT in 2019. 2) to systematize the process of student outcomes evaluation, and 3) to compare and analyze the results of the student outcomes evaluations with the same course and other courses with the same student outcomes in previous and new versions.

TABLE V
SUMMARY OF THE RESULTS OBTAINED

| Student Outcome | Performance Indicator | Unsatisfactory | Partially Satisfactory | Satisfactory | Excellent | Satisfactory + Excellent |
|---|---|---|---|---|---|---|
| Computer Knowledge (a) | a1 | 6.25% | 6.25% | 87.50% | 0.00% | **87.80%** |
| | a2 | 18.75% | 31.25% | 25.00% | 25.00% | 50.00% |
| Design and Development of Solutions (c) | c1 | 0.00% | 12.50% | 31.25% | 56.25% | **87.50%** |
| | c2 | 6.25% | 6.25% | 12.50% | 75.50% | **88.00%** |
| Individual and Team Work (d) | d1 | 6.25% | 12.50% | 37.50% | 43.75% | **81.25%** |
| | d2 | 6.25% | 43.75% | 31.25% | 18.75% | 50.00% |
| Communication (e) | e1 | 0.00% | 18.75% | 81.25% | 0.00% | **81.25%** |
| | e2 | 0.00% | 50.00% | 31.25% | 18.75% | 50.00% |

## REFERENCES


[1] Ashraf, D., 'Bio-inspired computing: Algorithms review, deep analysis, and the scope of applications', Future Computing and Informatics Journal, vol. 3, pp. 231-246, 2018.

[2] Devika, G. and Gowda Karegowda, A., 'Bio-inspired Optimization: Algorithm, Analysis and Scope of Application', Swarm Intelligence - Recent Advances and Current Applications. IntechOpen, Feb. 08, 2023.

[3] Holland, J. H., 'Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence'. U Michigan Press. 1975.

[4] Moscato, P. 'On Evolution, Search, Optimization, Genetic Algorithms and Martial Arts: Towards Memetic Algorithms'. C3P Report 826. California Institute of Technology. 1989.

[5] Murata, T. and Ishibuchi, H., 'MOGA: multi-objective genetic algorithms'. Proceedings of 1995 IEEE International Conference on Evolutionary Computation, Perth, WA, Australia, pp. 289-294, doi: 10.1109/ICEC.1995.489161. 1995.

[6] Koza, J.R., 'Genetic programming as a means for programming computers by natural selection', Stat Comput, vol. 4, pp. 87–112, 1994.

[7] Rechenberg, I., 'Cybernetic Solution Path of an Experimental Problem', Royal Aircraft Establishment Library Translation 1122, 1965.

[8] Fogel, D.B., 'Evolutionary programming: an introduction and some current directions', Stat Comput, vol. 4, pp. 113–129, 1994.

[9] Storn, R. and Price, K., 'Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces', Journal of Global Optimization, vol. 11, pp. 341–359, 1997.

[10] Dorigo, M. and Gambardella, L. M., 'Ant colony system: a cooperative learning approach to the traveling salesman problem', in IEEE Transactions on Evolutionary Computation, vol. 1, no. 1, pp. 53-66, April, 1997.

[11] Kennedy, J. and Eberhart, R., 'Particle swarm optimization', Proceedings of ICNN'95 - International Conference on Neural Networks, Perth, WA, Australia, vol.4, pp. 1942-1948, 1995.

[12] Karaboga, D., 'An Idea Based on Honey Bee Swarm for Numerical Optimization', Technical Report - TR06. Technical Report, Erciyes University, 2005.

[13] Castro, L.N. and Zuben, F.J., 'The Clonal Selection Algorithm with Engineering Applications' Genetic and Evolutionary Computation Conference, Workshop Proceedings of GECCO'00, Las Vegas, pp. 36-37, 2000.

[14] Forrest, S., Perelson, A. S., Allen, L. and Cherukuri, R. 'Self-Nonself Discrimination in a Computer'. In Proc. of the IEEE Symposium on Research in Security and Privacy, pages 202–212, 1994.

[15] Brabazon, A., O'Neill, M. and McGarraghy, S., 'Natural Computing Algorithms', Springer Publishing Company, Incorporated, 1st Editions, 2015.