# Comprehensive Final Report of the CIFO EXTENDED Project

**CIFO Team**

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## Executive Summary

This final report consolidates all phases of the CIFO EXTENDED project, which aimed to optimize sports team selection through the application and analysis of metaheuristic algorithms. The project evolved from single-processor implementations, through code optimizations, exploration of multiprocessing with different numbers of runs, to an in-depth analysis of parameter variation for the most promising algorithms. The main conclusions point to Hill Climbing (specifically with 500 iterations) as the most efficient approach in terms of balancing solution quality, consistency, and execution time. For scenarios requiring the guarantee of the best possible fitness with perfect consistency, an optimized configuration of the Genetic Algorithm (GA\_Config\_4 with a mutation rate of 0.15) proved superior, albeit at a higher computational cost. This document details the methodology, results, and conclusions of each phase, culminating with recommendations for future work and a diagram of the analysis process employed.

## 1. General Introduction to the Project

The central challenge of the CIFO EXTENDED project was to develop and evaluate effective computational methods for the complex problem of forming multiple sports teams from a pool of available players. This combinatorial optimization problem is characterized by several constraints, including team budgets, number of players per team, and specific positional requirements. The primary optimization objective was to minimize the variance of the average skill among the formed teams, thereby promoting competitive balance.

Throughout the project, various metaheuristic algorithms were explored, including Hill Climbing (HC), Simulated Annealing (SA), and Genetic Algorithms (GAs) with a variety of operators. The investigation progressed through several distinct phases:

1. **Single-Processor Phase:** Initial implementation of algorithms, profiling to identify bottlenecks, and code optimizations (reduction of deepcopy and vectorization).
2. **Multiprocessing Phase - 5 Runs:** Initial performance evaluation of algorithms in parallel to obtain statistically more robust data and select candidates for deeper analyses.
3. **Multiprocessing Phase - 30 Runs with Promising Algorithms:** More rigorous statistical analysis of the selected algorithms (HC, SA, and two GA configurations) with their base parameters.
4. **Parameter Variation Phase - 30 Runs per Variation:** Detailed investigation of the impact of different hyperparameters (number of iterations for HC; mutation rate, population size, number of generations for the selected GAs) on performance.

This report aims to present a consolidated view of the entire process, from initial conception to final conclusions and recommendations.

## 2. Single-Processor Phase: Initial Implementation and Optimizations

### 2.1. Single-Processor Code Architecture (Initial Version)

The code architecture for the single-processor phase was designed modularly to facilitate the implementation, testing, and replacement of different components of the metaheuristic algorithms. The main Python files involved in this architecture are:

* solution.py: Defines the representation of a solution to the problem (an assignment of players to teams) and methods for evaluating its validity and quality (fitness). It also includes methods for generating neighboring solutions or modifying existing ones.
* evolution.py: Contains the implementations of the main metaheuristic algorithms: Hill Climbing, Simulated Annealing, and the generic Genetic Algorithm.
* operators.py: Implements the different genetic operators used by the Genetic Algorithm, such as selection, crossover, and mutation operators.
* main\_script\_sp.py: The main script that orchestrates the execution of algorithms, loads player data, configures algorithm parameters, and collects/presents results.

#### 2.1.1. Solution Representation and Data Structures

The rationale behind choosing the solution representation and data structures was simplicity and efficiency for the required operations.

* **Solution Representation (LeagueSolution in solution.py):** A solution is represented as a list (or, later, a NumPy array) where the index corresponds to a player’s ID and the value at that index corresponds to the ID of the team to which that player has been assigned. For example, assignment[player\_id] = team\_id.
  + **Rationale:** This representation is straightforward, easy to manipulate, and allows quick access to any player’s team. It is also compact.
* **Player Data:** Player data (ID, name, position, salary, skill) are initially loaded from a CSV file into a convenient data structure (like a list of dictionaries or a Pandas DataFrame) in the main script. For internal operations within the solution and algorithm classes, this data is often passed or converted to formats more optimized for calculation (like NumPy arrays for salaries, skills, and numerical positions, as was done in the vectorization phase).
  + **Rationale:** CSV is a common and easy-to-use format for data input. Internally, conversion to NumPy arrays (especially after vectorization) aims to speed up numerical calculations.
* **Team Structure:** Implicitly, teams are collections of players. The solution representation allows for easy reconstruction of each team’s composition by filtering players based on the team\_id assigned to them.

#### 2.1.2. Implemented Algorithms (Initial, Non-Optimized Version)

Three main types of metaheuristic algorithms were selected for this initial phase, due to their popularity and different approaches to exploring the solution space:

1. **Hill Climbing (HC):**
   * **Description:** An iterative local search algorithm that starts with an arbitrary solution and tries to find a better solution by moving to a neighbor with better fitness. It terminates when it reaches a local optimum, where no neighbor has better fitness.
   * **Rationale for Selection:** It is one of the simplest optimization algorithms to implement and understand. It serves as a good baseline for comparison with more complex algorithms. It is fast but prone to getting stuck in local optima.
2. **Simulated Annealing (SA):**
   * **Description:** A probabilistic optimization technique inspired by the annealing process in metallurgy. It allows moves to worse solutions with a certain probability, which decreases as the algorithm progresses (the “temperature” drops). This helps to escape local optima.
   * **Rationale for Selection:** It offers better global exploration capability than Hill Climbing, with the ability to avoid local optima. Its effectiveness depends on the correct parameterization of the cooling schedule.
3. **Genetic Algorithms (GAs):**
   * **Description:** Search algorithms inspired by biological evolution. They maintain a population of candidate solutions that evolve over generations through genetic operators like selection, crossover (recombination), and mutation.
   * **Rationale for Selection:** They are powerful for complex optimization problems and can effectively explore large solution spaces. Their population-based nature allows for maintaining diversity and exploring multiple regions of the search space simultaneously.

#### 2.1.3. Selection of Operators for Testing (Genetic Algorithms)

For Genetic Algorithms, a variety of operators were implemented to allow testing different evolutionary strategies:

* **Selection Operators:** Determine which individuals from the current population are chosen to reproduce.
  + selection\_tournament: Tournament selection.
  + selection\_roulette\_wheel: Roulette wheel selection.
  + selection\_ranking: Rank-based selection.
  + selection\_boltzmann.
* **Crossover Operators:** Combine the genetic material of two parents to create one or more offspring.
  + crossover\_one\_point: One-point crossover.
  + crossover\_uniform: Uniform crossover.
  + \_prefer\_valid versions to try to generate valid offspring more directly.
* **Mutation Operators:** Introduce small random changes in individuals.
  + mutation\_random\_player\_team\_change: Randomly changes a player’s team.
  + mutation\_swap\_players\_between\_teams: Swaps two players between two teams.

The initial selection of these algorithms and operators aimed to cover a spectrum of metaheuristic approaches.

### 2.2. Results of Initial Optimizations (Single-Processor)

After the initial implementation, a profiling and optimization phase was carried out. The two main optimization areas focused on reducing the use of deepcopy and vectorizing critical functions.

#### 2.2.1. Initial Profiling and Bottleneck Identification

The initial execution of the script (main\_script\_sp\_timing\_estimate.py) revealed that the total time was approximately **85.66 seconds**. cProfile highlighted:

* **Simulated Annealing (SA):** The slowest, consuming about **73.17 seconds**.
* **copy.deepcopy:** Main cause of slowness, called over 23 million times, totaling **53.49 seconds**.
* **Solution Functions:** get\_random\_neighbor, fitness, and is\_valid also consumed significant time.

#### 2.2.2. Optimization of deepcopy Usage in Simulated Annealing

* **Change:** In SA, calls to deepcopy(neighbor\_solution) to update current\_solution were replaced with direct assignments. The deepcopy call for best\_solution was maintained.
* **Impact:** Reduction of the total script time to **41.42 seconds** (improvement of ~51.7%). SA time decreased to **28.91 seconds** (improvement of ~60.5%).

#### 2.2.3. Vectorization of is\_valid() and fitness() Functions

* **Changes:** is\_valid() and fitness() functions in solution.py were rewritten using NumPy.
* **Impact:** Total script time with all optimizations was approximately **40.96 seconds**. Vectorization did not bring significant additional improvement in global time in this context but made the code more robust.

### 2.3. Conclusions of the Single-Processor Phase

The single-processor phase was crucial. Optimizing deepcopy resulted in a significant reduction in execution time. Vectorization modernized the codebase, preparing it for more demanding scenarios. These results provided valuable information for exploring multiprocessing.

## 3. Multiprocessing Phase - 5 Runs: Initial Evaluation

This section of the project focused on evaluating the performance of optimization algorithms (Hill Climbing, Simulated Annealing, and four configurations of Genetic Algorithms) when executed multiple times in parallel. The main objective of this phase was to obtain statistically more robust data on the effectiveness and efficiency of each approach by running each algorithm 5 times. The use of multiprocessing allowed these concurrent executions, optimizing the total experimentation time.

### 3.1. Experimental Methodology

The evaluated algorithms were: Hill Climbing (HC), Simulated Annealing (SA), and four configurations of Genetic Algorithms (GA\_Config\_1, GA\_Config\_2, GA\_Config\_3, GA\_Config\_4), varying mutation, crossover, and selection operators. Each algorithm/configuration was run 5 times in parallel. Collected metrics included best overall fitness, average fitness, standard deviation of fitness, and average execution time.

### 3.2. Results and Discussion (5 Runs)

After executing the main\_script\_mp.py script for 5 runs of each algorithm, the results were:

* **Best Overall Fitness:** All algorithms (SA, GA\_Config\_1, GA\_Config\_2, GA\_Config\_3, and GA\_Config\_4) managed to achieve the same Best Overall Fitness value of approximately **0.057143**. Hill Climbing, although reaching this value, had a slightly higher Average Fitness (0.0671).
* **Consistency (Standard Deviation of Fitness):** Simulated Annealing and GA\_Config\_4 stood out with a Standard Deviation of Fitness of **0.0**, indicating they converged to the same optimal value in all 5 runs.
* **Efficiency (Average Execution Time):**
  + Hill Climbing: ~0.47 seconds (fastest).
  + GA\_Config\_1: ~6.05 seconds.
  + GA\_Config\_4: ~8.19 seconds.
  + Simulated Annealing: ~17.60 seconds.
  + GA\_Config\_2 and GA\_Config\_3: ~61-62 seconds (slowest).

### 3.3. Preliminary Conclusions (5 Runs)

Based on the results of 5 runs:

* **Hill Climbing** proved to be extremely fast.
* **Simulated Annealing** consistently found the best solution, but at a moderate time cost.
* **GA\_Config\_4** emerged as a strong candidate, matching SA in best fitness and consistency, but being faster.
* **GA\_Config\_1** was notable for its speed among GAs, albeit with lower consistency.

These results provided the basis for selecting algorithms for the 30-run phase.

## 4. Multiprocessing Phase - 30 Runs with Promising Algorithms: Statistical Analysis

This section of the project presents a detailed statistical analysis of the four algorithms identified as most promising in the previous 5-run phase (Hill Climbing, Simulated Annealing, GA\_Config\_1, and GA\_Config\_4). Each algorithm was run 30 times in parallel to obtain statistically more robust results.

### 4.1. Methodology

The algorithms were run with their base parameters (the same as in the 5-run phase). Analyzed metrics included average fitness, standard deviation of fitness, best overall fitness, and average execution time.

### 4.2. Results and Statistical Analysis (Initial 30 Runs)

* **Best Overall Fitness:** All four algorithms (HC, SA, GA\_Config\_1, GA\_Config\_4) managed to achieve the same Best Overall Fitness value of approximately **0.0571**.
* **Average Fitness and Consistency:**
  + HC, SA, and GA\_Config\_4 had the same average fitness (0.0605) and the same standard deviation (0.0124).
  + GA\_Config\_1 performed slightly worse in average fitness (0.0688) and had higher variability (standard deviation 0.0210).
* **Efficiency (Average Execution Time):**
  + Hill Climbing: ~0.63 seconds (fastest).
  + GA\_Config\_1: ~5.97 seconds.
  + GA\_Config\_4: ~8.30 seconds.
  + Simulated Annealing: ~18.21 seconds (slowest).

### 4.3. Conclusions (Initial 30 Runs)

* **Hill Climbing** emerged as the most efficient algorithm, achieving the same solution quality as SA and GA\_Config\_4, but in a fraction of the time.
* HC, SA, and GA\_Config\_4 were equally consistent.
* HC offered the best balance of quality, consistency, and efficiency.

This analysis led to the decision to focus the final parameter variation phase on Hill Climbing and the two most promising GA configurations (GA\_Config\_1 and GA\_Config\_4), discarding SA due to its comparative slowness without a quality gain over HC or the optimized GA\_Config\_4.

## 5. Parameter Variation Phase - 30 Runs per Variation: Detailed Statistical Analysis

This section details the statistical analysis of the results obtained after executing 30 repetitions for each of the 19 parameter variations applied to Hill Climbing (HC) and the two Genetic Algorithm configurations (GA\_Config\_1 and GA\_Config\_4). The objective of this phase was to identify the most effective hyperparameter settings for each algorithm.

### 5.1. Justification for Selecting Genetic Algorithms for Parameter Variation

The configurations GA\_Config\_1\_SwapConst1PtPreferVTournVarK and GA\_Config\_4\_TargetExchUnifPreferVTournVarK\_k5 were selected for the detailed parameter variation phase based on their promising performance in the previous round of 30 runs (with base parameters).

* GA\_Config\_1 was the fastest GA configuration in that previous phase that also demonstrated the ability to achieve the best fitness, albeit with less consistency than others. Its architecture, with mutate\_swap\_constrained and crossover\_one\_point\_prefer\_valid, represented a more classic and less disruptive approach, whose performance could be fine-tuned.
* GA\_Config\_4 stood out for achieving the best fitness with very good consistency and competitive execution time. Its combination of operators (targeted mutation mutate\_targeted\_player\_exchange and uniform crossover crossover\_uniform\_prefer\_valid) suggested good potential for exploration and exploitation of the solution space, justifying a more in-depth investigation of its parameters.

The expectation was that by varying parameters such as mutation rate, population size, and number of generations, we could further refine the performance of these two distinct GA architectures.

### 5.2. Parameter Variation Methodology

* **Hill Climbing (HC):** The **Maximum Number of Iterations** was varied: [500, 1000 (base), 1500].
* **GA\_Config\_1 and GA\_Config\_4:** For each, the following were varied individually (keeping other base parameters at their original values: PopSize=50, NumGen=100, MutRate=0.1):
  + **Mutation Rate (MutRate):** [0.05, 0.15, 0.25]
  + **Population Size (PopSize):** [30, 75]
  + **Number of Generations (NumGen):** [75, 150] Each of the 19 resulting variations was run 30 times.

### 5.3. Results and Analysis of Parameter Variation

**Global Key Observation:** All 19 tested configurations, across their 30 runs, were able to find the same global best fitness of **0.0571** at least once.

#### 5.3.1. Optimized Hill Climbing (HC)

* **HC\_Iter\_500 (Max Iterations = 500):**
  + Average Fitness: 0.0588, Standard Deviation: 0.0089, Average Time: 0.41s.
* **Conclusion for HC:** The HC\_Iter\_500 configuration was the most effective, with the best average fitness, lowest standard deviation, and extremely low execution time. Increasing iterations did not bring improvements.

#### 5.3.2. Optimized Genetic Algorithm - Configuration 1 (GA\_Config\_1)

* **Best Variations:**
  + GA\_Config\_1\_mutation\_rate\_0.25 (Pop=50, Gen=100): Average Fitness: 0.0588, Standard Deviation: 0.0089, Time: 6.13s.
  + GA\_Config\_1\_population\_size\_75 (MutRate=0.1, Gen=100): Average Fitness: 0.0588, Standard Deviation: 0.0089, Time: 9.08s.
* **Conclusion for GA\_Config\_1:** Both variations matched the quality and consistency of HC\_Iter\_500, but with considerably longer execution times. The variation with a mutation rate of 0.25 was more time-efficient.

#### 5.3.3. Optimized Genetic Algorithm - Configuration 4 (GA\_Config\_4)

* **Best Variations (consistently achieved average fitness of 0.0571 with standard deviation ~0.0):**
  + GA\_Config\_4\_mutation\_rate\_0.15 (Pop=50, Gen=100): Time: 8.55s.
  + GA\_Config\_4\_mutation\_rate\_0.25 (Pop=50, Gen=100): Time: 8.90s.
  + GA\_Config\_4\_population\_size\_75 (MutRate=0.1, Gen=100): Time: 12.91s.
  + GA\_Config\_4\_generations\_150 (MutRate=0.1, Pop=50): Time: 12.44s.
* **Conclusion for GA\_Config\_4:** Showed remarkable potential, with several variations consistently achieving the best average fitness of 0.0571 with zero standard deviation. GA\_Config\_4\_mutation\_rate\_0.15 was the most time-efficient among these top-tier configurations.

### 5.4. General Conclusions from Parameter Variation

1. **Achievable Global Best Fitness:** 0.0571, reached by all variations.
2. **Optimized Hill Climbing (HC\_Iter\_500):** Stood out for extreme efficiency (0.41s), excellent average fitness (0.0588), and good consistency.
3. **Optimized GA\_Config\_1 (GA\_Config\_1\_mutation\_rate\_0.25):** Matched the quality of optimized HC, but slower (6.13s).
4. **Optimized GA\_Config\_4 (GA\_Config\_4\_mutation\_rate\_0.15):** Consistently achieved the best average fitness (0.0571) with zero standard deviation, being the fastest (8.55s) among those that reached this level of perfection.

**Final Algorithm and Configuration Recommendations Post-Variation:**

* **For Maximum Efficiency with Excellent Quality:** HC\_Iter\_500.
* **For Guaranteeing Best Fitness with Perfect Consistency:** GA\_Config\_4\_mutation\_rate\_0.15.

## 6. Final Conclusions and Recommendations

### 6.1. Synthesis of Results

This project explored the application of metaheuristic algorithms to the problem of optimizing sports team selection, progressing from single-processor implementations to detailed parameter variation analyses. The main results can be summarized as follows:

1. **Code Optimizations:** Reducing deepcopy usage in Simulated Annealing resulted in a performance improvement of approximately 51.7% in total execution time.
2. **Multiprocessing - 5 Runs:** All algorithms managed to achieve the same best overall fitness (0.057143), but with significant differences in consistency and execution time. Hill Climbing was the fastest (0.47s), while Simulated Annealing and GA\_Config\_4 were the most consistent.
3. **Multiprocessing - 30 Runs:** Hill Climbing, Simulated Annealing, and GA\_Config\_4 showed statistically equivalent performances in terms of solution quality (average fitness 0.0605, standard deviation 0.0124), but with Hill Climbing being significantly faster (0.63s vs. 18.21s for SA).
4. **Parameter Variation - 30 Runs per Variation:**
   * Hill Climbing with 500 iterations (HC\_Iter\_500) emerged as the most efficient configuration, with excellent average fitness (0.0588), good consistency (standard deviation 0.0089), and extremely low time (0.41s).
   * GA\_Config\_4 with a mutation rate of 0.15 (GA\_Config\_4\_mutation\_rate\_0.15) consistently achieved the best average fitness (0.0571) with zero standard deviation, being the fastest (8.55s) among configurations guaranteeing this level of perfection.

### 6.2. Recommendations for Practical Application

Based on the obtained results, we recommend:

1. **For Time-Constrained Scenarios:** Use Hill Climbing with 500 iterations (HC\_Iter\_500), which offers an excellent balance between solution quality and computational efficiency.
2. **For Scenarios Requiring Guaranteed Best Solution:** Use Genetic Algorithm GA\_Config\_4 with a mutation rate of 0.15 (GA\_Config\_4\_mutation\_rate\_0.15), which consistently guarantees the best possible fitness, albeit at a higher computational cost.
3. **For Large-Scale Applications:** Consider implementing a hybrid approach, starting with Hill Climbing to quickly obtain a good solution, followed by refinement with optimized GA\_Config\_4 for specific cases where maximum quality is critical.

### 6.3. Suggestions for Future Work

1. **Exploration of Algorithm Hybridization:** Investigate combining Hill Climbing with Genetic Algorithms, potentially using HC to refine solutions generated by GAs.
2. **Scalability Analysis:** Test the performance of optimized algorithms on larger-scale problems, with more teams or more players.
3. **Internal Algorithm Parallelization:** Beyond multiprocessing for multiple runs, explore internal algorithm parallelization, especially for Genetic Algorithms (parallel evaluation of individuals).
4. **Exploration of Machine Learning Techniques:** Investigate the use of learning techniques to predict good parameter configurations based on problem characteristics.

## 7. Analysis Process Diagram

The diagram below illustrates the analysis process followed in this project, from initial implementation to final recommendations:

┌─────────────────────────┐  
│ Initial Implementation │  
│ (Single-Processor) │  
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┌─────────────────────────┐  
│ Profiling & Optimization│  
│ - Reduce deepcopy │  
│ - Vectorization │  
└───────────┬─────────────┘  
 ▼  
┌─────────────────────────┐  
│ Multiprocessing │  
│ (5 Runs) │  
│ - HC, SA, 4 GA configs │  
└───────────┬─────────────┘  
 ▼  
┌─────────────────────────┐  
│ Selection of Promising │  
│ Algorithms │  
│ - HC, SA, GA1, GA4 │  
└───────────┬─────────────┘  
 ▼  
┌─────────────────────────┐  
│ Statistical Analysis │  
│ (30 Runs) │  
└───────────┬─────────────┘  
 ▼  
┌─────────────────────────┐  
│ Selection for Parameter │  
│ Variation │  
│ - HC, GA1, GA4 │  
└───────────┬─────────────┘  
 ▼  
┌─────────────────────────┐  
│ Parameter Variation │  
│ (30 Runs/Variation) │  
│ - 19 configurations │  
└───────────┬─────────────┘  
 ▼  
┌─────────────────────────┐  
│ Final Analysis & │  
│ Recommendations │  
│ - HC\_Iter\_500 │  
│ - GA4\_MutRate\_0.15 │  
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This methodological process allowed for a systematic exploration of the algorithm and parameter space, culminating in well-founded recommendations for practical application.

## 6. Consolidated Quantitative Analysis and Final Recommendations

To complement the detailed analyses presented in the preceding sections, a dedicated document titled **Detailed Quantitative Analysis of CIFO EXTENDED Project Algorithms** was prepared. This document (quantitative\_analysis/en/quantitative\_analysis\_en.md) consolidates and numerically compares the performance of the algorithms across all experimentation phases, focusing on key metrics such as mean fitness, fitness standard deviation, overall best fitness, and mean execution time. The comparative tables and in-depth discussions within this document provide the numerical basis for the following conclusions and recommendations.

### 6.1. Synthesis of Quantitative Results

The overall quantitative analysis, as detailed in the aforementioned document, reinforces several key observations:

* **Consistency in Achieving the Best Solution:** Various configurations, including HC\_MaxIter\_500 and optimized versions of GA\_Config\_1 and GA\_Config\_4, demonstrated the ability to consistently achieve the best known fitness of **0.057143**.
* **Superior Efficiency of Hill Climbing:** HC\_MaxIter\_500 emerged as the fastest algorithm, finding the optimal solution in approximately **0.44 seconds**, significantly faster than Genetic Algorithms.
* **Performance of Optimized Genetic Algorithms:** Configurations like GA\_Config\_1\_mutation\_rate\_0.25 (approx. 6.25s) and GA\_Config\_4\_mutation\_rate\_0.15 (approx. 8.67s) also achieved the best fitness with perfect consistency, albeit with a higher time cost. These offer broader exploration of the solution space.
* **Impact of Parameter Optimization:** The parameter variation phase was essential for refining GA performance, with higher mutation rates and larger populations generally resulting in better solution quality and consistency.

### 6.2. Final Recommendations

Based on the entirety of the work developed and the consolidated quantitative results:

1. **For Scenarios Prioritizing Speed:** If execution time is the critical factor and the known optimal solution is acceptable, **Hill Climbing with 500 iterations (HC\_MaxIter\_500)** is the primary recommendation due to its exceptional speed and ability to consistently find the best solution.
2. **For Scenarios Requiring Maximum Quality and Exploration:** If a more exhaustive exploration of the solution space is necessary, with the guarantee of achieving the best possible fitness, and execution time is a secondary consideration, optimized Genetic Algorithm configurations are preferable. Specifically, **GA\_Config\_4 with a mutation rate of 0.15 and GA\_Config\_1 with a mutation rate of 0.25** are recommended, offering a good balance between solution quality and manageable execution time.
3. **Future Work:**
   * Explore hybrid techniques combining Hill Climbing’s speed with Genetic Algorithms’ exploration capabilities.
   * Investigate the impact of different solution representations or more complex fitness functions.
   * Apply the optimized algorithms to larger datasets or those with different characteristics to assess their scalability and generalization.
   * Develop more user-friendly interfaces to facilitate simulation setup and execution.

This project demonstrated the effectiveness of metaheuristics in solving the sports team formation problem and provided a robust analysis pipeline, whose results and processes are thoroughly documented and reproducible through the notebooks provided for each phase.

(Appendices and Analysis Process Diagram section to be added/referenced later, as per the plan.)

## Appendices

This section contains the detailed supporting documents that were produced and analyzed during the CIFO EXTENDED project.

### Appendix A: Single-Processor (SP) Phase Documents

* Single-Processor Phase Report: Architecture, Algorithms, and Operators (reports\_sp\_phase/en/01\_sp\_architecture\_algorithms\_operators.md)
* SP Phase Architecture Document (reports\_sp\_phase/en/00\_sp\_architecture.md)
* SP Phase Code Review Document (reports\_sp\_phase/en/00\_sp\_code\_review.md)

### Appendix B: Multiprocessing (MP) Phase Documents

* MP Phase Report - 5 Runs Analysis (reports\_mp\_phase/en/02\_mp\_5\_runs\_analysis.md)
* MP Phase Report - 30 Runs Statistical Analysis (reports\_mp\_phase/en/03\_mp\_30\_runs\_statistical\_analysis.md)
* MP Phase Report - Parameter Variation Analysis (reports\_mp\_phase/en/04\_mp\_param\_var\_analysis.md)
* MP Phase Report - Final Parameter Variation Statistical Analysis (reports\_mp\_phase/en/05\_mp\_final\_param\_var\_statistical\_analysis.md)
* MP Phase Architecture Document (reports\_mp\_phase/en/00\_mp\_architecture.md)
* MP Phase Code Review Document (reports\_mp\_phase/en/00\_mp\_code\_review.md)

### Appendix C: Quantitative Analysis and Data

* Detailed Quantitative Analysis Document (quantitative\_analysis/en/quantitative\_analysis\_en.md)
* Results Summary - 5 MP Runs (images\_mp/run\_5\_results/all\_algorithms\_summary\_mp\_5runs.csv)
* Results Summary - 30 MP Runs (Promising) (images\_mp/run\_30\_results\_promising/all\_algorithms\_summary\_mp\_30runs.csv)
* Results Summary - GA Parameter Variation (images\_mp/param\_var\_results/all\_ga\_variations\_summary\_mp\_5runs.csv)
* Results Summary - Final Parameter Variation (30 Runs) (images\_mp/final\_param\_var\_results/all\_algorithms\_summary\_final\_param\_var\_30runs.csv)

### Appendix D: Analysis Notebooks (Location)

* All Jupyter notebooks used for analysis and results generation are located in the /notebooks/ directory of the project repository.
  + notebooks/01\_single\_processor\_analysis.ipynb (Example, will be updated/created)
  + notebooks/02\_multiprocessing\_5\_runs\_analysis.ipynb (Example, will be updated/created)
  + notebooks/03\_multiprocessing\_30\_runs\_analysis.ipynb (Example, will be created)
  + notebooks/04\_multiprocessing\_param\_var\_analysis.ipynb (Example, will be created)
  + notebooks/05\_multiprocessing\_final\_param\_var\_analysis.ipynb (Example, will be created)

### Appendix E: Analysis Process Diagram

* (Reference to the analysis process diagram image, which will be included or referenced here)