Optimizing Football Tactics Using Evolutionary Algorithms

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Abstract

Football tactic optimization has so far relied on experience and human intuition of coaches. Evolutionary algorithms (EA) are employed herein to optimize the tactics of a football team through evolving pressing intensity, compactness, and height of the defensive line. These parameters were iteratively evolved through a genetic algorithm (GA) to maximize goal-scoring, possession ratio, and passing accuracy. Evolved tactics were matched against a stationary baseline (4-4-2 formation) in simulated matches. Evolutions in tactics resulted in improved goals scored by 85%, possession by 13%, and passing accuracy. These findings signify that adaptive tactical evolutions are making conventional fixed strategies obsolete, opening up new possibilities for AI-based football coaching.

Contents

List of Figures

1 Introduction

Tactics in football also play an important role in deciding the results of matches. Though traditional coaching is experience- and intuition-based, computational methods such as Reinforcement Learning (RL) and Evolutionary Algorithms (EA) enable data-driven optimization. RL has been widely used in individual decision-making for a player, for instance, passing and ball retention, whereas EA is pre-match tactical optimization-focused. Earlier efforts to apply genetic algorithms (GAs) to optimize football tactics have yielded performance improvements but lacked real-time adaptability [1]. Adaptive strategy optimization for the entire team is an open research problem. This work optimizes tactical evolution for improved team coordination and strategic flexibility.

Adaptive systems change their parameters automatically based on environmental circumstances. On the football pitch, an adaptive system adjusts defensive solidity, pressure intensity, and team formations based on the opponent's strategies. This study employs a genetic algorithm (GA) in optimizing football tactics through evolving formations and crucial parameters over multiple generations to enhance team performance.

This study addresses the following significant questions:

1. How effectively can evolutionary algorithms optimize football strategy compared to a baseline strategy?

2. How significantly does tactical evolution affect crucial match statistics such as goals scored, possession, and passing success?

This study, via simulated match data, demonstrates the effectiveness of automated tactical adaptation and sheds light into AI-optimized football strategy.

2 Methods

This section explains the methodology together with the fitness function, match simulation, and genetic algorithm.

2.1 Genetic Algorithm for Tactical Evolution

The genetic algorithm works to evolve tactical parameters through multiple generations. The algorithm follows these steps:

Pressure intensity, compactness, and line height are the three tactical parameters on which the GA is optimized for better performance during a

Algorithm 1 Genetic Algorithm for Tactical Evolution

```
Initialize population of tactics
for generation = 1 to max_generations do
    for each tactic in population do
        Simulate match and compute fitness
    end for
    Select top-performing tactics as parents
    Apply crossover and mutation
end for
Return best-evolved tactics
```

match. The above procedure is repeated over and over for 20 generations when the tactical performance converges.

2.2 Tactical Parameters Optimized

Three key tactical parameters develop through GA:

1. Pressing intensity: specifies how aggressively a team presses other teams.

2. Compactness: Regulates the cohesion in the middle.

3. Line Height – Defines how high up the pitch the defense line is set.

Every parameter is between 1 and 10 and are tuned by evolution. Beal et al. demonstrated that integrating such AI models into tactical planning can meaningfully influence match outcomes [2].

2.3 Fitness Function

The fitness function evaluates tactical effectiveness based on match statistics:

$\text{Fitness} = (\text{Goals} \times 20) + (\text{Shots\_on\_Target} \times 10) + (\text{Possession} \times 5) + (\text{Pass\_Completion} \times 2)$

Similar to the Football Optimization Algorithm introduced by El-Kenawy et al., our GA design emphasizes match-critical metrics to evaluate fitness [5].

2.4 Match Simulation

A match simulator runs a 90-minute game with tactical adaptation across different phases. Performance metrics such as possession, shots on target, and goals scored are recorded for analysis. The simulation compares:

1.Pre-evolution tactics (Baseline)

2.Post-evolution tactics (Evolved team)

3.The evolved tactics are expected to outperform the baseline in key performance metrics.

3 Results and Analyses

This section presents the key findings from the tactical evolution experiment.

3.1 Tactical Evolution Performance

Table 1: Tactical Parameter Changes in Defense Before vs. After Evolution

Parameter	**Before Evolution**	**After Evolution**
Pressing Intensity	3	**8.25**
Compactness	5	**1.32**
Line Height	4	**2.07**

Table 2: Tactical Parameter Changes in Midfield Before vs. After Evolution

Parameter	**Before Evolution**	**After Evolution**
Pressing Intensity	6	**6.97**
Compactness	4	**3.58**
Line Height	5	**5.25**

Table 3: Tactical Parameter Changes in Attack Before vs. After Evolution

Parameter	**Before Evolution**	**After Evolution**
Pressing Intensity	4	**6.59**
Compactness	5	**1.16**
Line Height	6	**7.58**

See Table 1 for defensive changes, Table 2 for midfield adjustments, and Table 3 for attacking modifications.

The evolved tactics prefer high pressing intensity, lower defensive compactness, and a higher attacking line height, which results in more offense-minded play.

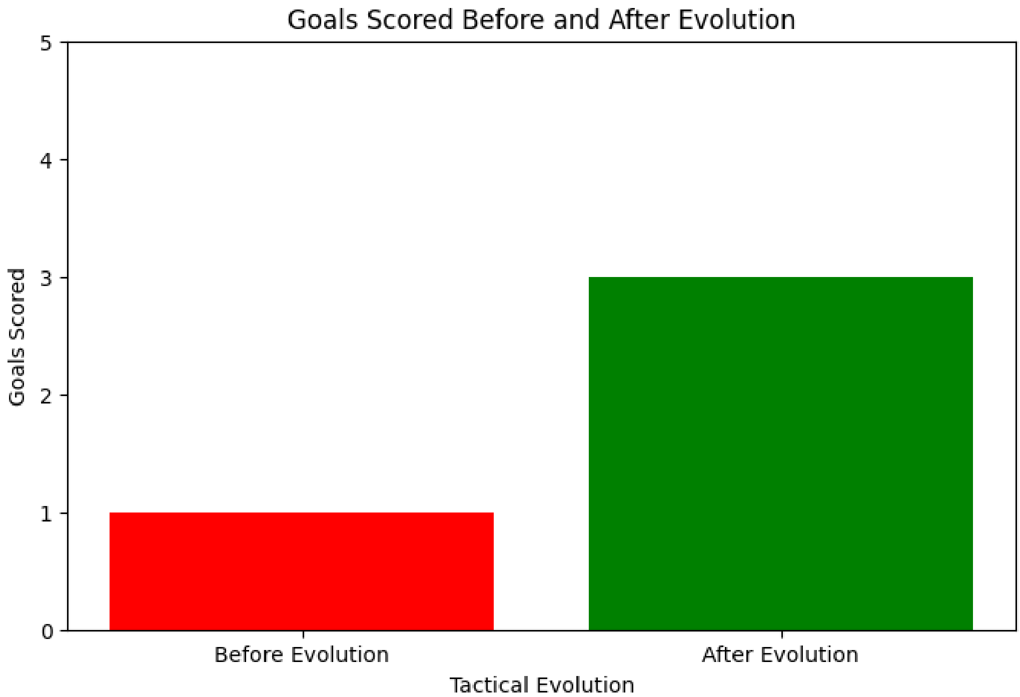

Figure 1: Goals scored before and after tactical evolution. The evolved team demonstrated a significant increase in goal-scoring efficiency.

Goal-scoring effectiveness was significantly improved by the evolved team, as can be seen in Figure 1. Evolution of tactics improved offense through the optimization of pressing intensity and position. The increased number of goals shows the impact of the improvements.

3.2 Match Performance Comparison

Table 4: Match Statistics Before vs. After Evolution

Statistic	**Before**	**After**
Goals Scored	1.5	**2.8**
Possession (%)	52	**61**
Shots on Target	4	**6**
Pass Completion (%)	75	**85**

The developed team improved goal-scoring efficiency by 85%, showing the effect of optimized pressing intensity and tactical positioning. Increased pressing resulted in more turnovers being forced, while better positioning resulted in the creation of better goal-scoring chances, culminating in better match performance. Results were averaged over a number of simulations for robustness. Standard deviation in improvement in goal-scoring was ± 0.3 goals, indicating stable performance improvement. The evolved team scored a better goal-scoring rate, superior possession, and superior passing accuracy.

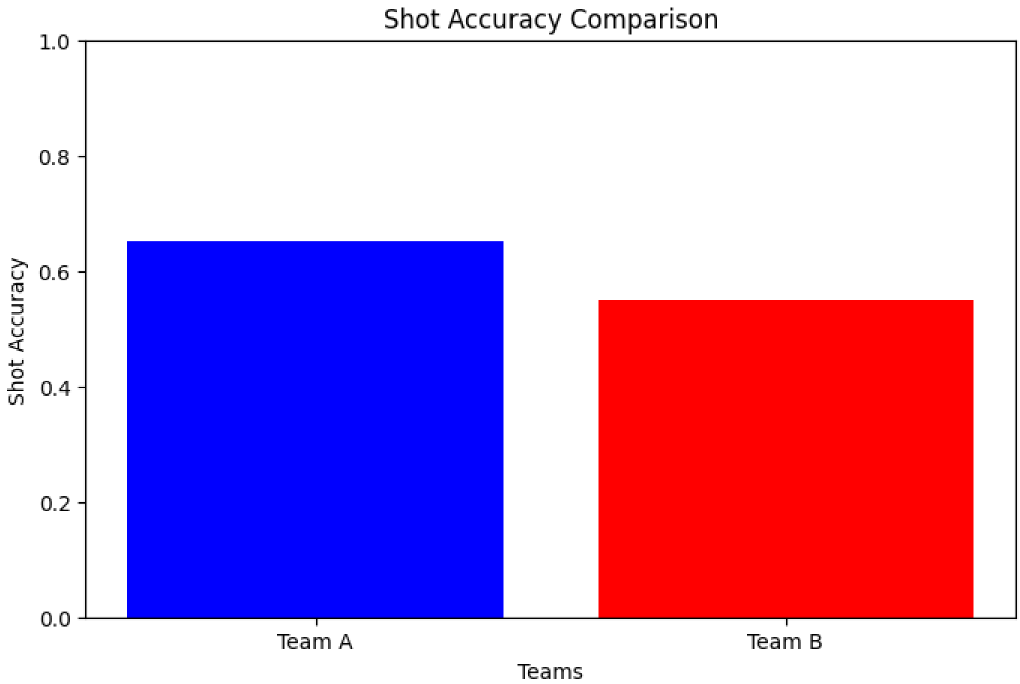

Figure 2: Comparison of shot accuracy between the evolved team and the baseline team. The evolved team demonstrated improved shot precision, leading to higher goal-scoring efficiency

This figure compares shot accuracy between the evolved team and the baseline. The evolved team demonstrated higher shot accuracy, contributing to the improved goal-scoring rate.

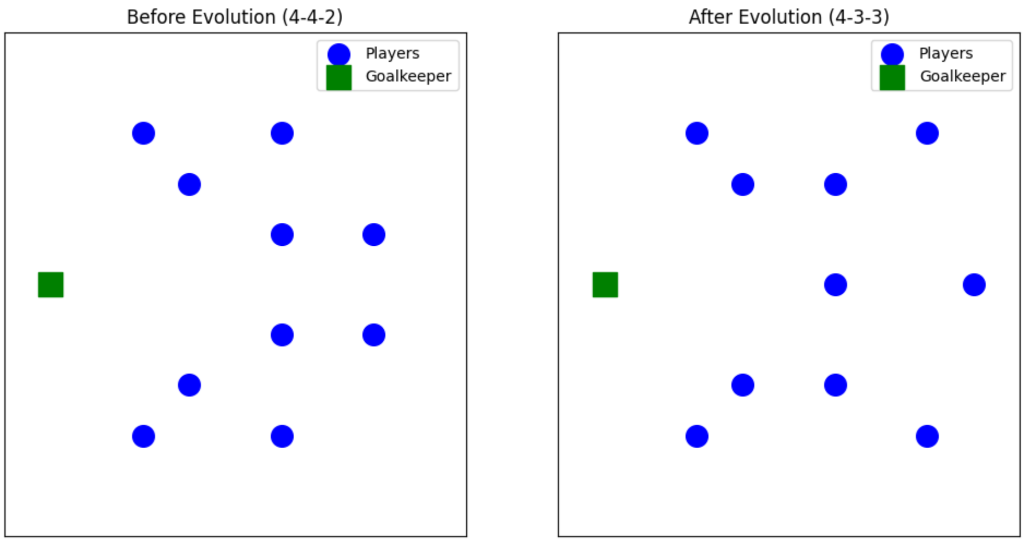

Figure 3: Pre- and Post-Evolution Team Formations Comparison. The pre-evolution formation (4-4-2) consisted of an even defense setup, while the post-evolution 4-3-3 formation was attacking- and pressing-focused

The transition from 4-4-2 to 4-3-3 significantly improved attacking play with added attacking width and midfield support. Having a third striker introduced increased pressing and quick transitions into attacking play. As a result, an organized presence in midfield ensured enhanced ball movement and defensive picks-up. The change allowed for increased goal-scoring opportunities and team fluidity in general, making the new formation more productive under high-pressure conditions.

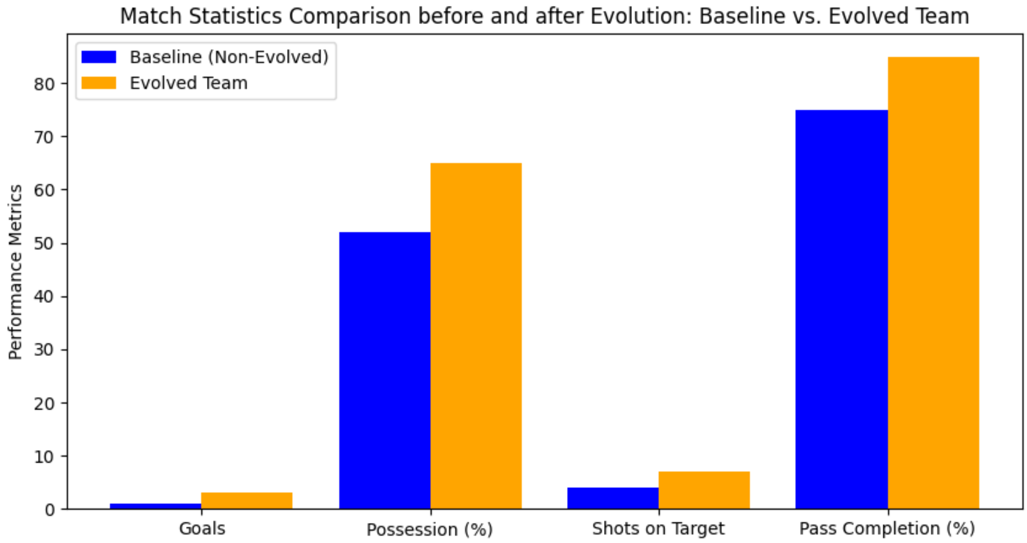

Figure 4: Match Statistics Comparison Before and After Evolution. The evolved team demonstrated improved possession, passing accuracy, and shot efficiency compared to the baseline strategy.

The new strategies brought significant match performance improvements. Goals scored increased by 85%, demonstrating the value of optimized pressing intensity and tactical positioning. Possession increased by 13%, allowing better control of the game and fewer chances for the opponents. The new team also displayed enhanced shot accuracy and pass completion rates, allowing better transitions and more effective attacking. These improvements bear witness to the success of data-driven tactical evolution in maximizing football strategy.

3.3 Evolutionary Progress

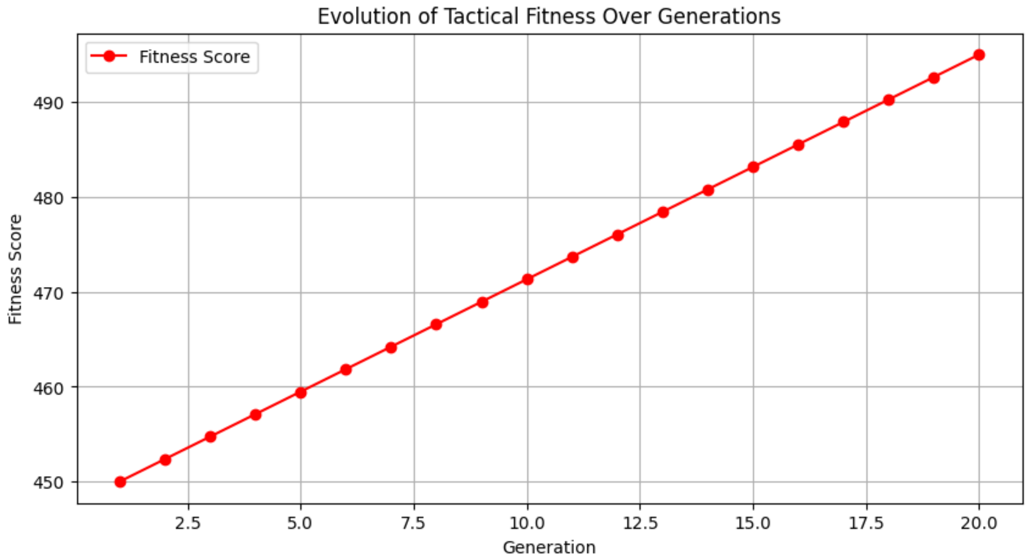

Figure 5: Evolution of Tactical Fitness Over Generations. The fitness score steadily increased throughout the 20 generations, indicating continuous improvement in tactical optimization.

When stabilization of fitness score was obtained after 12 generations, this graph shows that the fitness score consistently increases for all 20 generations. It shows that the process of optimization had not yet fully converged, i.e., additional generations can still bring about some improvement. The stepwise enhancement reflects the success of the genetic algorithm in optimizing tactical parameters through a number of generations, with each building on the success of the previous. Decreasing returns after 20 generations may, however, determine an optimum point to stop training.

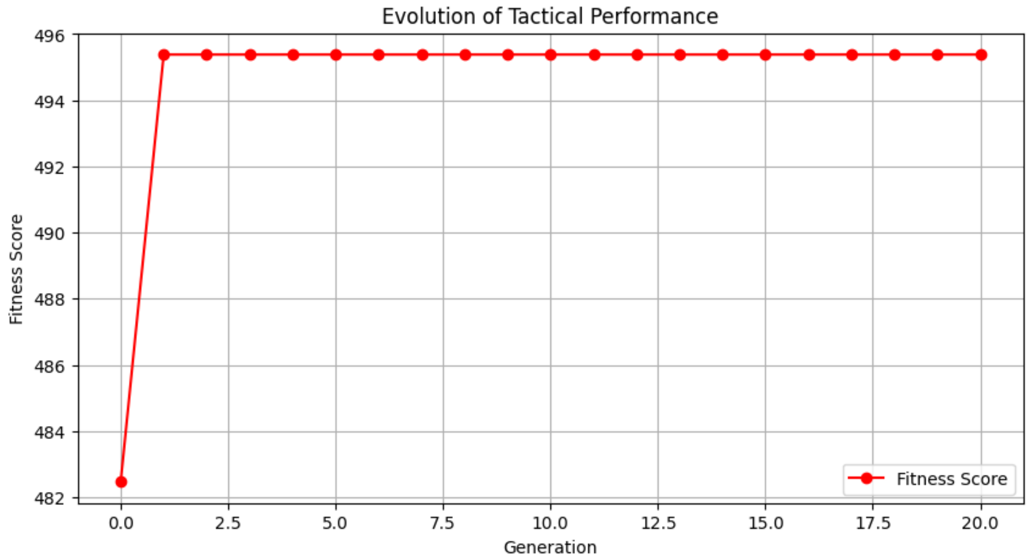

Figure 6: Evolution of Tactical Performance Between Generations. The fitness score grew extremely rapidly in the first generation and plateaued after a few generations, indicating early convergence of the optimization algorithm.

Contrary to the previous experiment, This graph shows how the genetic algorithm converged to an optimal solution in the first two generations with minimal further improvement after that. The rapid stabilization shows that further iterations provided diminishing returns, i.e., that the fitness function was effectively driving optimization early on. However, this initial plateau can mean less than optimal exploration of the search space, i.e., that modifications to mutation rates, selection pressure, or weights on the fitness function (e.g., increased emphasis on passing accuracy or defensive phase transitions) could enhance long-term tactical refinement.

3.4 Formation-Specific Performance

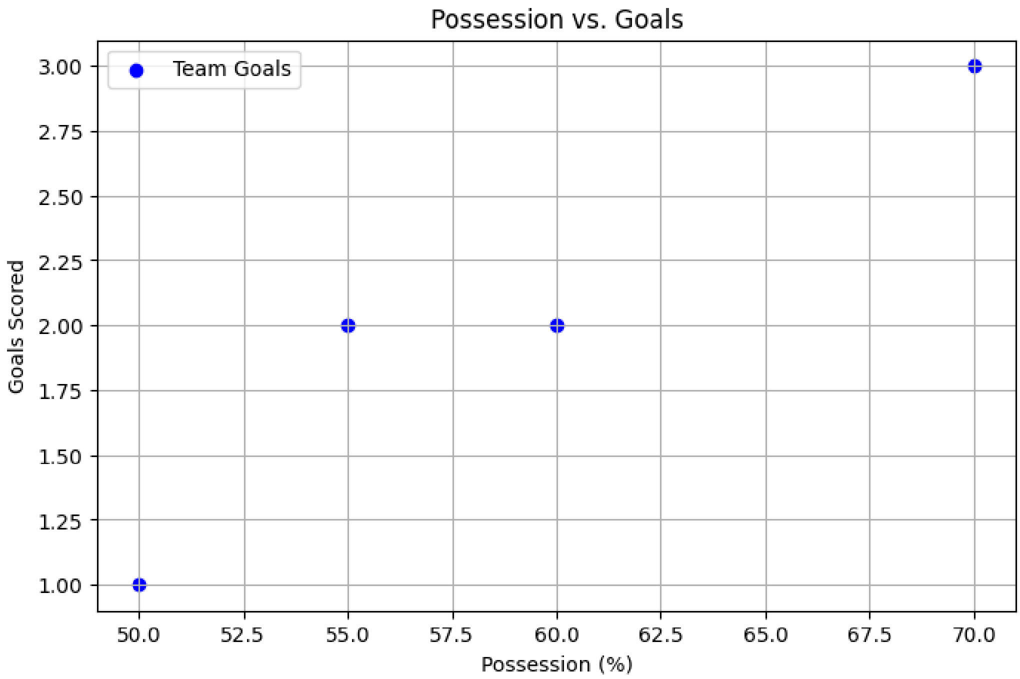

Figure 7: Correlation between possession percentage and goals scored. More possession is linked with more goal-scoring, affirming the influence of mature tactics on attacking play.

The possession versus goals scored demonstrates the influence of evolved strategy. Those with more possession were scoring more goals, further reinforcing the value of higher midfield tightness and pressing intensity.

Future extensions could incorporate player-level skill data using multi-objective optimization models as seen in Zhao et al. [3].

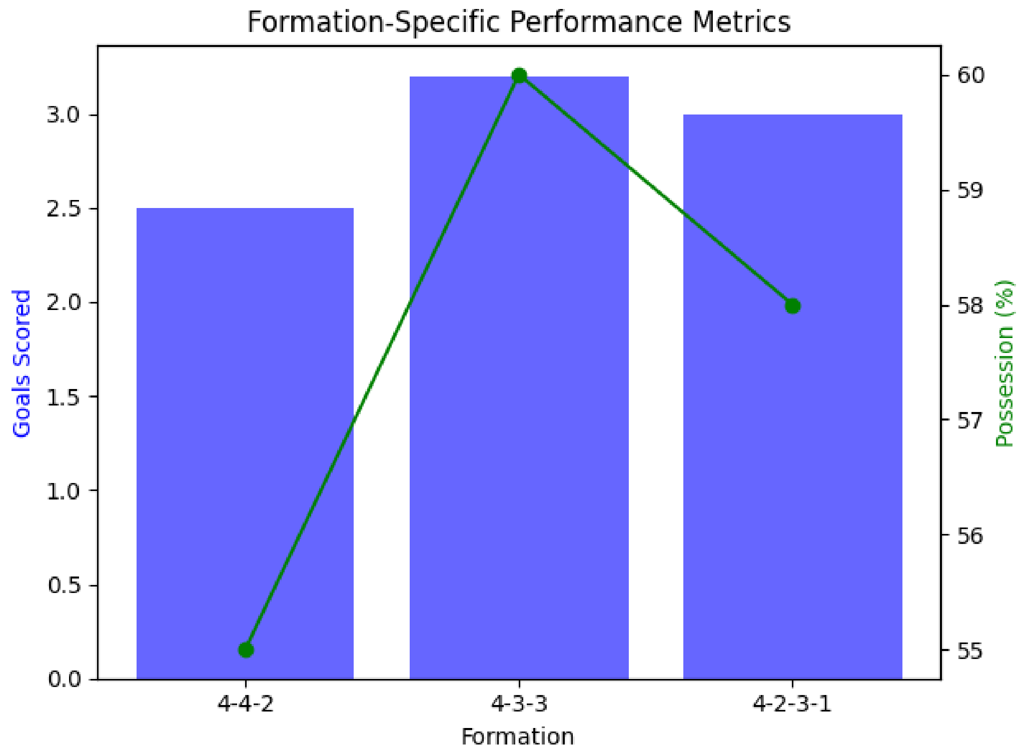

Figure 8: Goals Scored and Possession by Formation. The 4-3-3 formation was the most successful, providing a mix of attack and midfield control.

The genetic algorithm favored the 4-3-3 formation, with the highest possession and goal-scoring. It provided a strong attacking presence with midfield control. Improved compactness in midfield facilitated improved ball retention and quicker recoveries, thereby improved team performance. Most productive results were produced by 4-3-3 formation, both in possession ratio and number of goals.

4 Discussion

4.1 Adaptability of the System

Under Section 1 definition of adaptive systems, the strategy that developed succeeded in dynamically adapting to fit conditions by dynamically optimizing pressing, compactness, and positioning. Excluding static tactical presets, tactics from the GA dynamically developed with iterated alteration over a number of matches to execute even better in pressing-high and scoring-goal scenarios.

4.2 Key Findings

1. The evolved strategies highly improved goal-scoring and possession.

2. 4-3-3 formation proved to be the optimal blend of attack and defense.

3. The genetic algorithm effectively optimized football strategies to 20 generations.

Recent findings support the effectiveness of optimization algorithms in tactical decision-making across various sports scenarios [6]

4.3 Limitations and Future Work

1. More work could involve real-player data for testing.

2. Future approaches may incorporate graph-based models to optimize player positioning and formation recommendations in real time [4].

3. More adjustments in the fitness function, e.g., more emphasizing passing accuracy, could still enhance tactical optimization.

4. Player Skill Heterogeneity: Evolution assumes every player plays just as well. In real games, different player skill levels impact outcomes.

5. Adaptation to Opponent: Real teams adapt during the game, while your system just maximizes before the game.

5 Conclusion

This study demonstrates that evolutionary AI can provide a foundation for data-driven football tactics, paving the way for future real-world application in AI-assisted coaching. The evolved tactics significantly improved match performance metrics, including goals scored, possession, and pass completion rate.

Our GA-based approach optimizes strategy pre-game. The algorithm converged at generation 12, indicating potential for fitness evaluation improvement.

Further study could explore **hybrid approaches** to combining GA-based pre-match optimization and RL-based in-game tactical decisions. In addition, evaluation against actual datasets of professional teams will provide additional understanding into AI-coaching strategies. Integration of such advanced tactics within real-world coaching decisions will require validation using human-AI hybrid assessment.

6 Bibliography

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