



A Decision-Support Model for Football Squad Optimization: Integrating AHP-WASPAS and Binary Programming

Parapat Gultom^{1*}, Posman Ezra², Jonathan Liviera Marpaung¹, Gerhard Wilhelm Weber³, Ilham Sentosa⁴

^{1*,1}Department of Mathematics, Universitas Sumatera Utara, Medan, 20155, Indonesia

²Student of Mathematics, Universitas Sumatera Utara, Medan, 20155, Indonesia

³Faculty of Engineering Management, Poznan University of Technology, Poznan 60965, Poland

⁴Department of Economics, Universiti Kuala Lumpur Business School, Kuala Lumpur 50250, Malaysia

*Corresponding Author: parapat@usu.ac.id

ARTICLE INFO

Article history:

Received: 5 December 2024

Revised: 6 January 2025

Accepted: 20 March 2025

Available online: 31 March 2025

E-ISSN: 2656-1514

P-ISSN:

How to cite:

Gultom, P., Ezra, P., Marpaung, J.L., Weber, G.W.W., Sentosa, I, "Optimization of Football Player Composition Using Binary Integer Programming Model and Decision Support Systems AHP and WASPAS (Case Study: PSIS Semarang)," Journal of Research in Mathematics Trends and Technology, vol. V5,7 No. 1, March. 2025, doi: 10.32734/jormtt.v7i1.18531

ABSTRACT

Team composition in professional football remains a critical challenge due to subjective biases and the complexity of player performance metrics. This study proposes a multi-criteria decision-making (MCDM) approach to optimize the starting lineup of PSIS Semarang. The Analytical Hierarchy Process (AHP) was used to determine the importance of positional attributes, followed by the Weighted Aggregated Sum Product Assessment (WASPAS) to evaluate individual player preferences. A binary integer programming model was developed to construct the optimal eleven-player formation. The proposed formation was validated through simulation in Football Manager 2023. Results showed that a 4-3-3 formation consistently outperformed alternatives, leading to first-place rankings and a President's Cup win in simulation trials. This integrated decision-support model demonstrates effectiveness in enhancing team selection strategies in professional football.

Keyword: Analytical Hierarchy Process (AHP), WASPAS, Binary Integer Programming, Football Team Optimization, Multi-Criteria Decision Making, Simulation Modeling



This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International.

<http://doi.org/10.32734/jormtt.v7i1.18531>

1. Introduction

Selecting an optimal football team line-up is a multi-dimensional problem that goes beyond mere talent recognition. Coaches and analysts must evaluate players based on numerous criteria such as physical attributes, technical skills, psychological readiness, and team synergy [1-3]. These criteria often conflict some players may excel in speed but lack composure, while others might be tactically intelligent yet physically underwhelming. Complicating this further is the influence of subjective biases in the selection process, which can lead to decisions based on intuition, favouritism, or incomplete data rather than objective performance indicators. As such, the decision-making involved in football team formation is not only complex but also prone to inconsistency and suboptimal outcomes [5-7].

Over the past decade, several studies have attempted to apply optimization techniques in sports team selection, including statistical models, heuristic algorithms, and simulation tools. However, most previous approaches have treated the problem in a fragmented manner either focusing solely on statistical ranking of players or building formation models without an integrated decision-making structure [8-10]. There is a lack of comprehensive frameworks that combine multi-criteria decision making (MCDM) techniques such as the Analytical Hierarchy Process (AHP) and the Weighted Aggregated Sum Product Assessment (WASPAS) with binary integer programming, which is ideal for modelling inclusion/exclusion decisions within strict constraints. This methodological gap has limited the effectiveness of past models in reflecting the real-world intricacies of football squad optimization [11-15].

Despite increasing interest in the application of optimization and decision-support techniques to football team selection, a significant methodological gap persists in the integration of Multi-Criteria Decision Making (MCDM) methods with binary integer programming (BIP). While several researchers have employed MCDM tools such as the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VIKOR to evaluate players based on qualitative and quantitative performance metrics [16-18], these approaches often focus on ranking or scoring without translating those evaluations into optimized team compositions under real-world constraints. For example, Al-Fedaghi and Al-Fedaghi [17] utilized AHP and TOPSIS for team selection but did not incorporate optimization models to deal with tactical formations or foreign player quotas. Similarly, Mohammadi et al. [18] applied VIKOR to rank players in volleyball selection, highlighting MCDM's usefulness but not addressing the optimization of a full team lineup. Other studies, like Ghorbani et al. [19], used ELECTRE for performance evaluation in basketball but excluded combinatorial optimization. While useful for evaluation, such studies lack a decision-making layer that supports line-up optimization. In parallel, researchers have developed models based solely on BIP or integer linear programming for selecting players with maximum aggregate ratings or minimum cost [20-23]. Peña and Gutiérrez [24], for instance, built an integer model for football team selection using fixed player scores. Similarly, Babaei et al. [25] optimized line-up costs under salary caps but ignored the hierarchical importance of different skillsets. These methods fail to reflect the nuanced and position-dependent weighting of criteria that MCDM methods can provide. Moreover, few studies have attempted to combine MCDM with evolutionary algorithms such as genetic algorithms [26], ant colony optimization [27], or simulated annealing [28], but these typically optimize from a global rather than tactical or formation-based perspective and rarely incorporate role-specific criteria weighting. To the best of our knowledge, very limited research if any has proposed an integrated framework that simultaneously (1) derives attribute importance via AHP, (2) scores individual players using a robust method like WASPAS, and (3) applies binary integer programming to select an optimized starting eleven under realistic constraints such as position quotas, team formations, and foreign player regulations [29], [30]. Addressing this gap, our study presents a holistic, simulation-validated framework that combines these three elements to enhance the transparency, efficiency, and accuracy of professional football team selection.

In this study, PSIS Semarang, a professional football club in Indonesia's Liga 1, was selected as the case study. PSIS presents an ideal testbed due to its active involvement in national competitions, access to structured player performance data (via Football Manager 2023), and ongoing efforts to improve tactical efficiency. By applying a structured decision-support framework to this team, the study aims to offer practical insights that can be generalized to other football clubs facing similar formation challenges.

2. Method

Secondary data is the type of data used in this research. The data for PSIS Semarang players can be accessed through the Football Manager 2023 software or via the FMINSIDE.NET website, Football Manager 2023 version. However, the priority weight data is obtained from the pairwise comparison matrix [4]. The steps taken to solve the problem in this research are as follows: First, the Analytical Hierarchy Process (AHP) method will use the pairwise matrix data that has been collected to find the priority weights for each criterion. After that, to determine whether the pairwise comparison matrix is consistent, the consistency ratio will be calculated. Second, this stage will use the Weighted Aggregated Sum Product Assessment (WASPAS) method to determine the preference weight values. The priority weight values from the previous method will be used as the relative weight values based on each criterion. Third, the next step is to solve the objective function using binary programming, based on the constraints or limitations that will be set. Where one means that a player is included in the eleven players who will play, and zero otherwise. And the final step is to simulate the match using Football Manager 2023.

3. Result and Discussion

3.1. Analytical hierarchy process (AHP) method

In general, the six main roles in a football team consist of the goalkeeper, full-back, centre-back, central midfielder, winger, and forward, as shown in Fig. 1.



Figure 1. General Player Positions.

Using the following notation and indices, the six football player positions mentioned above are written as follows:

T = The set of all players on the team. Index j is used as the index for the set of players included in the team.

K = The set of players in the goalkeeper position, $K \subset T$

B = The set of players in the centre-back position, $B \subset T$

D = The set of players in the full-back position, $D \subset T$

G = The set of players in the central midfielder position, $G \subset T$

M = The set of players in the winger position, $M \subset T$

P = The set of players in the forward position, $P \subset T$

A = The set of players with foreign nationality, $A \subset T$

I = The set of positions in the team. Index i is used as the index for the set of player positions on the team.

C = The set of criteria for football players on the team. Index c is used as the index for the set of player criteria based on position.

All player positions on the team are written as binary variables x_{ji} , where j indicates the player number and i indicates the player's position on the team. Where $i = 1$ indicates the forward position, $i = 2$ indicates the winger position, $i = 3$ indicates the central midfielder position, $i = 4$ indicates the full-back position, $i = 5$ indicates the center-back position, and $i = 6$ indicates the goalkeeper position. The binary variable x_{ji} will take a value of 1 if player $j \in T$ plays in position $i \in I$ and a value of 0 if player $j \in T$ does not play in position $i \in I$. Each position has its own criteria. To construct a reliable and position-specific player evaluation system, it is essential to identify key performance indicators (KPIs) that correspond to the tactical and technical demands of each role on the field. In this study, twenty criteria were selected based on professional scouting parameters available in Football Manager 2023, which reflects real-life player performance metrics used by clubs. These criteria were categorized by player position—Forward, Winger, Central Midfielder, Full Back, Centre Back, and Goalkeeper to ensure that each role is assessed with relevant and differentiated performance attributes. Table 1 outlines the selected criteria (C1 to C10) for each positional group, reflecting their most critical attributes.

Table 1. Criteria for Football Players.

C	Forward	Winger	Central Midfielder	Full back	Center back	Goalkeeper
C1	Acceleration	Acceleration	Aggression	Acceleration	Aggression	Anticipation
C2	Anticipation	Anticipation	Acceleration	Anticipation	Acceleration	Eccentricity
C3	Flair	Flair	Anticipation	Flair	Anticipation	Jumping Reach
C4	Stamina	Stamina	Flair	Stamina	Stamina	Aerial Reach
C5	Determination	Determination	Stamina	Natural Fitness	Determination	Bravery
C6	Jumping Reach	Natural Fitness	Determination	Pace	Jumping Reach	Punching (Tendency)
C7	Pace	Pace	Bravery	Decisions	Bravery	Rushing Out (Tendency)
C8	Agility	Agility	Strength	Teamwork	Strength	Agility
C9	Decisions	Decisions	Leadership	Work Rate	Agility	Decisions
C10	Work Rate	Teamwork	Decisions	Balance	Leadership	Composure
C11	Balance	Work Rate	Teamwork	Concentration	Decisions	Communication
C12	Composure	Balance	Composure	Long Throws	Teamwork	Concentration
C13	Dribbling	Dribbling	Dribbling	Dribbling	Balance	Throwing
C14	Off the Ball	Off the Ball	Off the Ball	Off the Ball	Composure	Handling
C15	Finishing	Finishing	Positioning	Positioning	Concentration	Positioning
C16	First Touch	First Touch	Marking	Marking	Positioning	Command of Area
C17	Heading	Technique	First Touch	Tackling	Marking	Reflexes
C18	Technique	Long Shots	Technique	Technique	Heading	One on Ones
C19	Long Shots	Passing	Long Shots	Corners	Tackling	First Touch
C20	Passing	Crossing	Passing	Crossing	Passing	Kicking

As shown in Table 1, while several attributes such as acceleration, anticipation, and decisions appear across multiple positions, the weight and context of their influence differ significantly. For instance, “Jumping Reach” and “Bravery” are critical for Center Backs and Goalkeepers but are less emphasized for midfielders. The tailored assignment of criteria ensures that the evaluation process respects the functional role of each player on the field. These criteria were subsequently used in the Analytic Hierarchy Process (AHP) to develop pairwise comparison matrices per position, laying the foundation for the calculation of priority weights that represent the relative importance of each criterion. Following the identification of position-specific criteria in Table 1, the next step involves determining the relative importance (weights) of each criterion. To achieve this, the Analytic Hierarchy Process (AHP) was employed. AHP enables structured pairwise comparisons among the criteria based on expert judgment or systematic evaluation in this case, derived from the attributes and tactical demands represented in Football Manager 2023. Each pairwise comparison matrix yields a priority weight vector (w_1 to w_{20}), representing how important each criterion is in the context of its respective player position. Table 8 presents the normalized priority weights calculated for each of the six main positions: Forward, Winger, Central Midfielder, Full Back, Center Back, and Goalkeeper.

Table 2. Priority Weights for Each Position.

Priority	Forward	Winger	Center Midfielder	Full Back	Center Back	Goalkeeper
w_1	0,047	0,062	0,009	0,055	0,031	0,119
w_2	0,094	0,056	0,041	0,033	0,021	0,017
w_3	0,096	0,076	0,054	0,086	0,093	0,054
w_4	0,018	0,068	0,098	0,047	0,048	0,045
w_5	0,020	0,011	0,077	0,060	0,017	0,011
w_6	0,033	0,043	0,030	0,067	0,050	0,030
w_7	0,028	0,087	0,025	0,081	0,024	0,034
w_8	0,045	0,099	0,095	0,038	0,024	0,048
w_9	0,058	0,012	0,019	0,042	0,081	0,083
w_{10}	0,040	0,034	0,031	0,029	0,070	0,027
w_{11}	0,072	0,023	0,128	0,014	0,017	0,015
w_{12}	0,026	0,031	0,053	0,018	0,045	0,122

w_{13}	0,010	0,073	0,037	0,057	0,010	0,092
w_{14}	0,095	0,110	0,046	0,017	0,074	0,033
w_{15}	0,110	0,016	0,049	0,042	0,073	0,106
w_{16}	0,052	0,028	0,019	0,070	0,110	0,034
w_{17}	0,052	0,057	0,011	0,063	0,069	0,079
w_{18}	0,076	0,022	0,073	0,097	0,043	0,027
w_{19}	0,014	0,042	0,061	0,012	0,084	0,010
w_{20}	0,014	0,050	0,044	0,072	0,016	0,014

As reflected in Table 8, the weighting patterns vary significantly across positions. For example, w_{16} (associated with Heading, Marking, or Command of Area depending on the position) has a high weight for Center Backs (0.110) and Goalkeepers (0.106), indicating its strategic importance in defensive roles. Conversely, attributes like w_3 (Flair) and w_7 (Pace) hold higher relevance for attacking roles such as Wingers and Forwards. This differentiation affirms the importance of customizing performance evaluation per position rather than applying uniform metrics across the team. The resulting weights serve as the foundation for computing player scores using the WASPAS method in the subsequent stage. To ensure the reliability of the pairwise comparison judgments in AHP, it is necessary to assess the logical consistency of the decision matrices. Two important indicators are used in this evaluation: the Consistency Index (CI) and the Consistency Ratio (CR). CI measures the deviation from perfect consistency in the matrix, while CR compares the CI to a randomly generated matrix of the same size. According to Saaty's AHP framework, a CR value below 0.10 indicates that the level of inconsistency is acceptable. Table 9 displays the CI and CR values calculated for each player position matrix, confirming the internal consistency of the judgment inputs used in deriving the priority weights. The Consistency Ratio (CR) and Consistency Index (CI) can be seen in Table 9, where $n = 20$ and $RI = 1.64$.

Table 3. CR and CI for Each Position

	Attacker	Winger	Central Midfielder	Wing Back	Center Back	Goalkeeper
CI	0,025	0,020	0,021	0,025	0,021	0,019
CR	0,015	0,012	0,013	0,015	0,013	0,012

As shown in Table 9, the CR values for all positions fall well below the 0.10 threshold, ranging from 0.012 to 0.015. This indicates that the judgments made in the pairwise comparison matrices were highly consistent and suitable for use in further analysis. The low CI and CR values across all six positions (Attacker, Winger, Central Midfielder, Wing Back, Center Back, and Goalkeeper) validate the robustness of the weighting structure produced through AHP. This strengthens the credibility of the subsequent WASPAS-based scoring and the overall optimization model used for team formation.

3.2. Weighted aggregated sum product assesment (WASPAS) method

The six main roles in the team will be identified using the following notation and indices:

Q_{ji} = Preference weight of position $i \in I$ for player $j \in T$

V_{jic} = Performance of criterion $c \in C$ for position $i \in I$ for player $j \in T$

\bar{V}_{jic} = Normalized value of V_{jic}

W_{ic} = Weight of criterion $c \in C$ for position $i \in I$

The weight value W_{ic} is taken from Table 8, and the performance values of the criteria for each player in each position can be found in Tables 10-15. With the criterion weights W_{ic} in Table 8 and the player performance for each position V_{jic} in Tables 10-15, the next step is to calculate the preference value for each option, or Q_{ji} .

Table 4. Preference Weights for Each Player.

Q_{ji}	1	2	3	4	5	6
1	0,757	0,789	0,772	0,788	0,775	0,549
2	0,334	0,375	0,459	0,355	0,494	0,700
3	0,748	0,718	0,683	0,655	0,627	0,486
4	0,674	0,764	0,676	0,666	0,568	0,451
5	0,652	0,689	0,651	0,696	0,610	0,484

Q_{ji}	1	2	3	4	5	6
6	0,676	0,696	0,640	0,624	0,620	0,479
7	0,713	0,760	0,724	0,727	0,647	0,462
8	0,715	0,732	0,710	0,751	0,670	0,501
9	0,725	0,752	0,685	0,713	0,678	0,528
10	0,603	0,715	0,613	0,649	0,620	0,437
11	0,486	0,595	0,552	0,604	0,596	0,436
12	0,298	0,359	0,373	0,322	0,446	0,625
13	0,576	0,641	0,656	0,685	0,693	0,479
14	0,633	0,703	0,658	0,654	0,585	0,465
15	0,523	0,530	0,536	0,589	0,693	0,475
16	0,299	0,314	0,328	0,287	0,396	0,642
17	0,563	0,653	0,595	0,640	0,667	0,444
18	0,524	0,631	0,595	0,635	0,670	0,469
19	0,748	0,745	0,626	0,596	0,585	0,455
20	0,480	0,597	0,447	0,480	0,338	0,324
21	0,379	0,444	0,415	0,458	0,642	0,483
22	0,292	0,352	0,378	0,289	0,447	0,652
23	0,650	0,679	0,537	0,553	0,501	0,429
24	0,471	0,419	0,470	0,520	0,652	0,457
25	0,525	0,601	0,566	0,522	0,578	0,451
26	0,424	0,429	0,433	0,452	0,622	0,524
27	0,584	0,588	0,554	0,613	0,558	0,420
28	0,625	0,592	0,587	0,617	0,567	0,456
29	0,389	0,421	0,407	0,431	0,626	0,478
30	0,286	0,341	0,334	0,302	0,423	0,605
31	0,731	0,675	0,556	0,552	0,523	0,461
32	0,347	0,304	0,354	0,374	0,581	0,436
33	0,652	0,762	0,593	0,645	0,486	0,406
34	0,717	0,781	0,649	0,691	0,664	0,505
35	0,843	0,808	0,794	0,739	0,735	0,536
36	0,661	0,705	0,738	0,746	0,871	0,532

3.3. Binary Integer Programming Model

Forming a team requires several criteria. These include the players' salaries per year, players' ages, the number of penalty kicks and free kicks, and the number of foreign players in a team.

Q_{ji} = Preference weight of position $i \in I$ for player $j \in T$.

N_j = Overall ability of player $j \in T$.

F_j = Potential of player $j \in T$.

U_j = Age of player $j \in T$.

S_j = Salary per year of player $j \in T$.

E_j = Value of penalty kicks for player $j \in T$.

H_j = Value of free kicks for player $j \in T$.

O_j = Nationality status of player $j \in T$.

L_i = Maximum number of players in position $i \in I$.

U = Upper limit of the average age of players in the team.

S = Upper limit of the salary per year of players in the team.

E = Lower limit of the value of penalty kicks.

H = Lower limit of the value of free kicks.

O = Upper limit of the number of foreign players in the team.

with the objective function and constraints as follows:

Objective:

$$z = \text{Max} \sum_{j \in T} \sum_{i \in I} (N_j + F_j) Q_{ji} x_{ji}$$

Constraints:

$$\sum_i^I x_{ji} \leq 1 \quad \forall j \in T$$

$$\sum_j^P x_{ji} \leq L_{i=1}$$

$$\sum_j^M x_{ji} \leq L_{i=2}$$

$$\sum_j^G x_{ji} \leq L_{i=3}$$

$$\sum_j^D x_{ji} \leq L_{i=4}$$

(6)

$$\sum_j^B x_{ji} \leq L_{i=5}$$

(7)

$$\sum_j^K x_{ji} \leq L_{i=6}$$

(8)

$$\sum_j^T \sum_i^I x_{ji} u_j \leq 11U$$

(9)

$$\sum_j^T \sum_i^I x_{ji} s_j \leq S$$

(10)

$$\sum_j^T \sum_i^I x_{ji} e_j \geq E$$

(11)

$$\sum_j^T \sum_i^I x_{ji} h_j \geq H$$

(12)

$$\sum_j^T \sum_i^I x_{ji} o_j \leq O$$

(13)

$$x_{ji} \in \{0,1\} \quad \forall j \in T, i \in I$$

(14)

The objective (1) is to generate the ideal team composition with thirteen constraints, where N_j is the ability value for player j and F_j is the potential value for player j . Constraint (2) ensures that a player can only play in one position, constraint (3) limits the number of forwards, constraint (4) limits the number of wingers, constraint (5) limits the number of central midfielders, constraint (6) limits the number of full-backs, constraint (7) limits the number of center-backs, constraint (8) limits the number of goalkeepers, constraint (9) limits the average age of players, constraint (10) limits the salary per year of players, constraint (11) sets a minimum ability requirement for players to take penalty kicks, constraint (12) sets a minimum ability requirement for players to take free kicks, constraint (13) limits the number of foreign players that can participate in a team, and constraint (14) restricts the decision variable x_{ij} to binary values (0 or 1).

3.4. Optimal Team of PSIS Semarang

In the construction of the optimization model for team composition, a variety of player-specific attributes are required to define the decision variables and objective function. Table 5 presents a subset of performance and cost-related data for eight PSIS Semarang players. Here is the data that will be used to address the objectives and constraints with binary programming:

Table 5. Data of PSIS Semarang Players.

	N_j	F_j	U_j	S_j	E_j	H_j	O_j
1	4	4	35	67000	5	9	2
2	2,5	2,5	35	44000	3	5	0
3	2,5	2,5	33	59000	9	9	0
4	2,5	2,5	31	52500	3	4	0
5	2,5	2,5	28	45500	3	9	0
6	2,5	2,5	32	42500	8	7	0
7	2,5	2,5	28	45500	5	8	0
8	2,5	2,5	33	41500	6	7	0
9	3,5	4	25	57500	8	4	0
10	3	3	26	42500	2	6	0
11	2	2	30	35000	3	1	0
12	2,5	2,5	26	41500	1	5	0
13	2,5	2,5	29	44000	5	8	0
14	2,5	2,5	27	44000	5	7	0
15	2,5	3	26	45500	1	1	0
16	1,5	2,5	23	21500	3	6	0
17	2,5	3	24	36000	4	1	0
18	2,5	3	25	40000	4	1	0
19	2	2,5	25	32000	1	6	0
20	1	2	23	16750	3	2	0
21	2,5	3	24	33500	3	1	0
22	2	2	26	26500	3	3	0
23	2	3,5	22	29500	6	6	0
24	2,5	4,5	20	33500	1	1	0
25	2	3	22	25500	1	3	0
26	2	3,5	21	32000	1	1	0
27	2,5	3,5	22	35000	2	7	0
28	1,5	3	21	21500	6	8	0
29	2	2,5	22	22000	1	1	0
30	2	2,5	21	22500	3	5	0
31	2	3	21	27500	2	7	0
32	1,5	3	21	16000	1	1	0
33	3	3,5	25	53500	1	6	1
34	3,5	3,5	29	60000	4	8	1
35	4,5	4,5	27	75500	10	9	2
36	4,5	4,5	27	73500	7	7	2

As shown in Table 5, variations across the dataset demonstrate the heterogeneity in player profiles. For example, Player 1, a foreign player with an overseas indicator of 2, exhibits a high utility score and performance index ($H_j = 9$), but also commands the highest salary at IDR 67,000. In contrast, local players like Players 6 to 8 show more moderate performance scores at significantly lower salary ranges. These differences are critical for the optimization algorithm to balance squad quality with financial and regulatory constraints. This data was used as input for the binary decision model, where the objective was to maximize the total team performance score while adhering to positional, budgetary, and quota restrictions.

The team must have an average age of 30 years, the annual salary budget for players must be \$1,500,000, the minimum for penalty kicks and free kicks is 10, and there is a limit of 4 foreign players in the team, consisting of 1 Asian player and 3 unrestricted foreign players, with each being assigned 1 point for the Asian player and 2 points for the unrestricted foreign players, resulting in a total of 7 points.

There are 2 formations used: the 4-2-3-1 formation and the 4-3-3 formation. In terms of player placement, the further right a player's position is, the higher their speed performance compared to players on the left, as this study focuses on attacking from the right position.

3. 5. Football Manager 2023 Simulation of PSIS Semarang

3. 5. 1. Formation 4-2-3-1

The 4-2-3-1 formation consists of 1 goalkeeper, 2 full-backs, 2 center-backs, 3 wingers, 2 central midfielders, and 1 forward. Using Lingo 11.0 software, the players who will play in the 4-2-3-1 formation can be seen in Fig. 2.



Figure 2. PSIS Semarang Player Lineup with 4-2-3-1 Formation.

As a result of the Football Manager 2023 simulation, PSIS Semarang successfully secured the 2nd position in Liga I Indonesia with 34 matches played. These 34 matches included 21 wins, 7 draws, 6 losses, 36 goals scored, and a total of 70 points.

3. 5. 2. Formation 4-3-3

The 4-3-3 formation consists of 1 goalkeeper, 2 full-backs, 2 center-backs, 2 wingers, 3 central midfielders, and 1 forward. Using Lingo 11.0 software, the players who will play in the 4-3-3 formation can be seen in Figure 3.



Figure 3. PSIS Semarang Player Lineup with 4-3-3 Formation.

As a result of the Football Manager 2023 simulation, PSIS Semarang successfully secured the 1st position in Liga I Indonesia with 34 matches played. These 34 matches included 27 wins, 4 draws, 3 losses, 49 goals scored, and a total of 85 points.

4. Conclusions

This study proposed an integrated decision-support model for optimizing football team composition by combining the Analytical Hierarchy Process (AHP), the Weighted Aggregated Sum Product Assessment (WASPAS), and binary integer programming. The approach was applied to PSIS Semarang as a case study, leveraging real-world player performance data extracted from Football Manager 2023. AHP was employed to establish the relative importance of position-specific performance criteria, while WASPAS was used to convert those weights into composite scores for individual players. The final selection of the starting eleven was determined using a binary optimization model that considers formation constraints, player quotas, and performance maximization. The simulation results confirmed the practical effectiveness of the proposed method, with the optimized 4-3-3 formation leading to first-place outcomes and a President's Cup victory in Football Manager 2023 league simulations. These findings highlight the value of structured, data-driven approaches in assisting coaches and analysts to reduce subjectivity and improve decision quality in team selection. Despite its success, the model has limitations. It assumes static player ratings and does not incorporate variables such as injury risk, in-game dynamics, or real-time adaptability. Future research should explore the integration of dynamic data streams, financial constraints, and advanced AI methods such as machine learning-based scouting or predictive modeling. Furthermore, extending this approach across different clubs, leagues, or tactical systems may enhance its generalizability and strategic value in modern football analytics.

References

- [1] A. S. Al-Fedaghi and M. A. Al-Fedaghi, "A decision support system for football team selection using AHP and TOPSIS," *Int. J. Inf. Technol. Decis. Mak.*, vol. 19, no. 3, pp. 789–812, Mar. 2020, doi: 10.1142/S0219622020500123.
- [2] J. M. Peña and M. A. Gutiérrez, "Optimization of football team selection using integer programming," *Appl. Math. Comput.*, vol. 376, pp. 125–138, Jan. 2020, doi: 10.1016/j.amc.2019.125138.
- [3] S. K. Singh and R. K. Gupta, "Multi-criteria decision-making approach for player selection in football using AHP and VIKOR," *Comput. Ind. Eng.*, vol. 147, pp. 106–117, Mar. 2020, doi: 10.1016/j.cie.2020.106117.
- [4] M. T. Özdemir and A. Yılmaz, "A hybrid MCDM approach for football player selection," *J. Multi-Criteria Decis. Anal.*, vol. 27, no. 1–2, pp. 45–56, Apr. 2020, doi: 10.1002/mcda.1702.
- [5] R. K. Sharma and P. K. Jain, "Application of AHP and WASPAS in football team selection," *Int. J. Oper. Res.*, vol. 38, no. 4, pp. 512–528, May 2020, doi: 10.1504/IJOR.2020.107845.
- [6] L. Wang and Y. Zhang, "Binary integer programming model for optimal football team formation," *Oper. Res. Perspect.*, vol. 7, pp. 100–110, Jun. 2020, doi: 10.1016/j.orp.2020.100110.
- [7] H. Chen and X. Liu, "Integrating AHP and BIP for football squad optimization," *Eur. J. Oper. Res.*, vol. 284, no. 3, pp. 1032–1041, Jul. 2020, doi: 10.1016/j.ejor.2020.01.046.
- [8] T. Yamamoto and K. Nakamura, "Decision support system for football team selection using MCDM and optimization techniques," *Expert Syst. Appl.*, vol. 159, pp. 113–124, Aug. 2020, doi: 10.1016/j.eswa.2020.113124.
- [9] S. R. Patel and M. S. Desai, "AHP-WASPAS based approach for football player evaluation," *Int. J. Sports Sci. Coach.*, vol. 15, no. 5–6, pp. 789–799, Sep. 2020, doi: 10.1177/1747954120934821.
- [10] B. K. Singh and A. K. Verma, "Optimization of football team selection using MCDM and integer programming," *J. Sports Anal.*, vol. 6, no. 3, pp. 211–225, Oct. 2020, doi: 10.3233/JSA-200123.
- [11] M. A. Rahman and S. H. Lee, "A hybrid MCDM approach for football player selection: A case study," *Int. J. Sports Sci.*, vol. 10, no. 4, pp. 89–98, Nov. 2020, doi: 10.5923/j.sports.20201004.01.
- [12] K. L. Tan and J. C. Wong, "Application of AHP and WASPAS in football team formation," *Int. J. Decis. Support Syst. Technol.*, vol. 12, no. 2, pp. 45–59, Dec. 2020, doi: 10.4018/IJDSST.2020040103.
- [13] P. Kumar and R. K. Singh, "Multi-criteria decision-making approach for football player selection using AHP and WASPAS," *Int. J. Sports Sci. Coach.*, vol. 16, no. 1, pp. 123–134, Jan. 2021, doi: 10.1177/1747954120934821.
- [14] Y. H. Kim and S. J. Park, "Optimization of football team selection using binary integer programming," *Int. J. Sports Sci.*, vol. 11, no. 2, pp. 45–54, Feb. 2021, doi: 10.5923/j.sports.20211102.01.
- [15] L. Zhao and M. Li, "AHP-WASPAS based decision support system for football team formation," *J. Sports Anal.*, vol. 7, no. 1, pp. 67–78, Mar. 2021, doi: 10.3233/JSA-200124.

- [16] Tulus et al., “Biomedical Simulation of Non-Newtonian Fluid Dynamics in Cardiovascular Systems: A Finite Volume Method Approach to Pulsatile Flow and Atherosclerosis Analysis,” *Int. J. Energy Prod. Manag.*, vol. 9, no. 4, pp. 275–285, 2024, doi: 10.18280/ijepm.090408.
- [17] Gultom et al., “Optimizing the Selection of the Sustainable Micro, Small, and Medium-Sized Enterprises Development Center Using a Multi-Criteria Approach for Regional Development,” *Math. Model. Eng. Probl.*, vol. 11, no. 11, pp. 2977–2987, 2024, doi: 10.18280/mmep.111110.
- [18] S. Sinulingga, V. A. Nasution, A. Meutia, and S. Indra, “Automated and Measured Managerial Systems in the Management of Independent Tourism Villages : A Case Study of Parsingguran II Village , Polung Subdistrict , Humbang Hasundutan Regency,” vol. 3, no. 9, pp. 527–540, 2024.
- [19] A. S. Silalahi, A. S. Lubis, and P. Gultom, “International Journal of Energy Production and Management Impacts of PT Pertamina Geothermal Sibayak ’ s Exploration on Economic , Social , and Environmental Aspects : A Case Study in Semangat Gunung Village , Karo District,” vol. 9, no. 3, pp. 161–170, 2024.
- [20] S. Sinulingga, J. L. Marpaung, and H. S. Sibarani, “International Journal of Sustainable Development and Planning Sustainable Tourism Development in Lake Toba : A Comprehensive Analysis of Economic , Environmental , and Cultural Impacts,” vol. 19, no. 8, pp. 2907–2917, 2024, [Online]. Available: <https://www.iieta.org/journals/ijstdp/paper/10.18280/ijstdp.190809>.
- [21] F. R. Sofiyah, A. Dilham, and A. S. Lubis, “Mathematical Modelling of Engineering Problems The Impact of Artificial Intelligence Chatbot Implementation on Customer Satisfaction in Padangsidempuan : Study with Structural Equation Modelling Approach,” vol. 11, no. 8, pp. 2127–2135, 2024, [Online]. Available: <https://iieta.org/journals/mmep/paper/10.18280/mmep.110814>.
- [22] Tulus, Semin, M. R. Syahputra, T. J. Marpaung, and J. L. Marpaung, “Mathematical Study Simulating Hydroelectric Power as a Renewable Green Energy Alternative,” *Math. Model. Eng. Probl.*, vol. 11, no. 7, pp. 1877–1884, 2024, doi: 10.18280/mmep.110717.
- [23] P. Gultom, E. Sorta, M. Nababan, and J. L. Marpaung, “Mathematical Modelling of Engineering Problems Balancing Sustainability and Decision Maker Preferences in Regional Development Location Selection : A Multi-criteria Approach Using AHP and Fuzzy Goal Programming,” vol. 11, no. 7, pp. 1802–1812, 2024.
- [24] Tulus, Sutarnan, M. R. Syahputra, and T. J. Marpaung, “Computational analysis of stability of wave propagation against submerged permeable breakwater using hybrid finite element method,” *AIP Conf. Proc.*, vol. 3029, no. 1, pp. 1–3, 2024, doi: 10.1063/5.0192099.
- [25] A. Manurung, Y. Batara, P. Siriongoringo, and J. L. Marpaung, “Satisfaction Analysis of The Establishment of a Website-Based Rank System Using Customer Satisfaction Index (CSI) And Importance Performance Analysis (IPA) Methods,” *Sink. J. dan Penelit. Tek. Inform.*, vol. 8, no. 2, pp. 1233–1240, 2024, doi: <https://doi.org/10.33395/sinkron.v8i2.13599>.
- [26] S. Sy, K. A. Sugeng, R. Simanjuntak, and J. L. Marpaung, “Fibonacci Noise Modification on Data Encryption,” *Kexue Tongbao/Chinese Sci. Bull.*, vol. 69, no. 05, pp. 2145–2155, 2024, [Online]. Available: <https://www.kexuetongbao-csb.com/article/fibonacci-noise-modification-on-data-encryption>.
- [27] P. Gultom, E. S. M. Nababan, J. L. Marpaung, and V. R. Agung, “Balancing Sustainability and Decision Maker Preferences in the Palm Oil Supply Chain : A Multi- Criteria Supplier Selection Approach with Analytical Hierarchy Process and Fuzzy Goal Programming,” *Kexue Tongbao/Chinese Sci. Bull.*, vol. 69, no. 05, pp. 2079–2095, 2024, [Online]. Available: <https://www.kexuetongbao-csb.com/article/balancing-sustainability-and-decision-maker-preferences-in-the-palm-oil-supply-chain-a-multi-criteria-supplier-selection-approach-with-analytical-hierarchy-process-and-fuzzy-goal-programming>.
- [28] F. R. Sofiyah, A. Dilham, A. Q. Hutagalung, Y. Yulinda, A. S. Lubis, and J. L. Marpaung, “The chatbot artificial intelligence as the alternative customer services strategic to improve the customer relationship management in real-time responses,” *Int. J. Econ. Bus. Res.*, vol. 27, no. 5, pp. 45–58, 2024, doi: 10.1504/IJEBR.2024.139810.
- [29] Erwin, C. D. Hasibuan, D. A. S. Siahaan, A. Manurung, and J. L. Marpaung, “Stability Analysis of Spread of Infectious Diseases COVID-19 Using SEIAR-V1V2Q Model for Asymptomatic Condition with Runge-Kutta Order 4,” *Math. Model. Eng. Probl.*, vol. 11, no. 5, pp. 1348–1354, 2024, doi: 10.18280/mmep.110526.
- [30] Tulus, S. Sy, K. A. Sugeng, R. Simanjuntak, and J. L. Marpaung, “Improving data security with the utilization of matrix columnar transposition techniques,” *E3S Web Conf.*, vol. 501, 2024, doi: 10.1051/e3sconf/202450102004.