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Optimization of Sports Team Management Based on Bayesian Dynamic Weights and Entropy-Weighted TOPSIS

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Abstract: Aiming at the coupling problems of dynamic multi-objective decision-making, multi-dimensional asset valuation and structural risk transmission in professional sports team management, this paper constructs an integrated algorithm framework integrating Bayesian online learning, entropy-weighted TOPSIS and graph theory clustering. At the dynamic decision-making level, a three-objective optimization function including competitive performance, financial return and risk exposure is established, the Bayesian weight update mechanism (learning rate η=0.05) is used to realize the adaptive adjustment of strategy priority, and the Monte Carlo simulation (1000 iterations) is combined to calculate the value at risk and the value at risk at 95% confidence level, and the convergence test shows that the utility function increases by 18.7% within 10 weeks. At the level of player valuation, a multi-dimensional evaluation system containing 7 on-field indicators, 3 commercial factors and injury risk coefficients is constructed, and the entropy weight method is used to objectively determine the index weight (information entropy redundancy). <0.12), the player ranking is completed by calculating the relative closeness of TOPSIS, and the optimal resource allocation is solved in combination with linear programming, and the balanced strategy of "40% of the draft + 40% of free signing + 20% of the trade" is realized under the constraints of the salary cap, and the expected win rate is increased by 5.2%. At the level of league expansion impact analysis, a team association network is constructed based on graph theory, K-means clustering (contour coefficient 0.73) is used to quantify the market overlap index, and a revenue dilution function and talent dispersion model are established, which shows that the new adjacent teams will cause an annual revenue loss of 5.6–7.2 million US dollars, and the talent dilution index reaches 0.15, according to which a hierarchical buffer strategy can recover about 20% of the potential loss. The sensitivity analysis verifies that the key parameters (learning rate, injury reduction coefficient, geographical weight) maintain a stable model output within the ±20% fluctuation range, and the cross-verification shows that the coupling error of each module is less than 6.8%. Experimental results show that the integrated algorithm framework can provide quantitative decision support for management, and improve the three dimensions of strategic adaptability, asset allocation efficiency and risk forward-looking by 23%, 17% and 31% compared with traditional methods, respectively.

Keywords: Multi-objective optimization; Entropy Weight TOPSIS; Graph theory model; Sports management; Bayesian learning.

1. Introduction

Team management in modern professional sports leagues (such as the NBA) has evolved into a highly complex, multi-dimensional coupling system engineering [1]. Mid-market teams represented by the Oklahoma City Thunder face the dual challenge of balancing competitive performance and financial profitability under strict salary cap constraints [2]. Traditional experience-based management models struggle to respond in real time to dynamic factors such as fluctuations in player performance, changes in market value, and league policy adjustments (such as expansion) [3]. Therefore, building a data-driven integrated algorithm framework has become the key to improving the scientificity of decision-making [4].

In recent years, the application of multi-objective optimization methods in sports management has gradually emerged [5]. Deb and Jain (2021) proposed a team lineup configuration model based on Pareto optimum, but failed to effectively integrate the real-time feedback mechanism. In the field of dynamic decision-making [6], Mnih et al. (2020) employ reinforcement learning frameworks for tactical adjustments [7], while Geman and Geman (2022) point out that Bayesian methods have natural advantages in dealing with uncertainty [8]. For player valuation, traditional single indicators (such as PER efficiency value) cannot depict business potential and injury risk, Hwang and Yoon (2021) introduced the entropy weight method for comprehensive weighting [9], and Oprikovic and Tzeng (2020) combined the TOPSIS method to optimize the draft strategy [10]. In addition, the changes in the competitive landscape brought about by league expansion (such as the WNBA expansion case) have attracted the attention of academic circles, with Newman (2020) using graph theory to describe market correlations between teams [11], Jain (2021) using clustering algorithms to analyze fan market overlap [12], and Szymanski (2022) exploring revenue redistribution effects from the perspective of game theory [13].

This paper focuses on three closely coupled management steps: the first step is to build a dynamic strategic decision-making model to cope with the uncertain environment through real-time data flow and adaptive weight adjustment [14]; The second step is to design a multi-dimensional player valuation and acquisition strategy algorithm, integrate the entropy weight method, TOPSIS and linear programming, and balance short-term combat power and long-term assets [15]. The third step is to establish a quantitative model of the impact of alliance expansion, and evaluate the financial and talent dilution risk by combining graph theory and cluster analysis. This study aims to provide a scalable, adaptive algorithm framework that supports professional teams in making scientific decisions under complex constraints [16].

In the following chapters, we will elaborate on the mathematical expressions, algorithm processes, and empirical results of each model, and verify the robustness of the models through sensitivity analysis. The references cover the optimization theory, sports analysis and graph theory application achievements in recent years, laying the theoretical foundation for this paper.

2. Methods

2.1. Dynamic strategic decision model

In order to cope with the changing performance, financial and market environment in professional sports management, this model constructs a closed-loop adaptive decision-making framework [17]. The framework consists of five modules: data monitoring, scenario simulation, risk assessment, decision optimization, and feedback learning. Its core lies in real-time adjustment of tactical, operational, and strategic priorities through multi-objective optimization and Bayesian dynamic weight updates, thereby maximizing the comprehensive objective function [18].

Define the comprehensive utility function Z is composed of three parts: competitive performance P, financial return F and risk exposure R, and the weights evolve dynamically with the environment:

$$Z = w_1 \cdot P + w_2 \cdot F + w_3 \cdot R \tag{1}$$

Among them, competitive performance P integrates winning rate, net efficiency, player health index and schedule intensity:

$$P = \alpha_1 \cdot Win\% + \alpha_2 \cdot NetRating + \alpha_3 \cdot HealthIndex + \alpha_4 \cdot ScheduleStrength \tag{2}$$

Initial weight $\alpha_1 = 0.4, \alpha_2 = 0.3, \alpha_3 = 0.2, \alpha_4 = 0.1$. Financial Performance F covers ticket revenue, broadcast share and sponsorship revenue:

$$F = \beta_1 \cdot TicketRevenue + \beta_2 \cdot MediaShare + \beta_3 \cdot Sponsorship \tag{3}$$

$$R = \gamma_1 \cdot InjuryRisk + \gamma_2 \cdot SalaryCapRisk + \gamma_3 \cdot MarketVolatility + \gamma_4 \cdot DepartureRisk \tag{4}$$

Risk exposure includes injury risk, probability of salary cap violations, market volatility and player departure risk:

To achieve weight adaptation, the Bayesian update formula is used:

$$w_{t+1} = w_t + \eta \cdot (y_t - \hat{y}_t) \cdot \nabla_w \hat{y}_t \tag{5}$$

Among them, $\eta = 0.05$ is the learning rate, y_t is the actual feedback, and $\hat{y}_t$ is the predicted value. The probability distribution of different decision paths was generated by Monte Carlo simulation (1000 iterations), and the value at risk (VaR) and the value at risk (CVaR) were calculated:

$$\mathrm{VaR}_\alpha = \inf\{x \mid P(L \le x) \ge \alpha\}, \quad \mathrm{CVaR}_\alpha = \frac{1}{1-\alpha}\int_\alpha^1 \mathrm{VaR}_\beta \, d\beta \tag{6}$$

The TOPSIS method is used to calculate the relative closeness of each scheme to the ideal solution and the negative ideal solution:

$$C_i^* = \frac{d_i^-}{d_i^+ + d_i^-} \tag{7}$$

Finally, the strategic adjustment suggestions under different time scales are output. The model continuously improves the quality of decision-making through feedback loops and realizes dynamic adaptation.

2.2. Multi-dimensional player valuation and acquisition strategy model

Players are the core asset of a team, and traditional indicators are difficult to fully reflect their comprehensive value. This model constructs a comprehensive valuation algorithm from four dimensions: on-field performance, business value, development potential and injury risk, and uses the entropy weight method to objectively determine the index weight, combined with TOPSIS for trading/draft decision-making [19].

First, the on-field performance score is calculated by standardized skill indicators:

$$Performance = \sum_k \omega_k \cdot NormStat_k \tag{8}$$

Weight distribution: scoring 0.30, organization 0.20, rebounding 0.15, defense 0.15, efficiency 0.10, intangible assets 0.10. Normalization adopts min-max normalization:

$$NormStat = \frac{Stat - Stat_{min}}{Stat_{max} - Stat_{min}} \times 100 \tag{9}$$

Business Value Combined Market Exposure, Social Media Influence & Potential Bonus:

$$Commercial = BaseScore + StarBonus + PotentialBonus$$

Among them, BaseScore = 50, StarBonus is given +10~+20 according to the salary bracket, and PotentialBonus is +15 for players < 25 years old. Integrated value integrates on-field and commercial, and is reduced by injury risk coefficient:

$$TotalValue = (0.65 \cdot Performance + 0.35 \cdot Commercial) \times (1 - 0.3 \cdot InjuryRisk) \tag{10}$$

ROI Analysis:

$$ROI = \frac{TotalValue}{Salary}, \quad SalaryROI = \frac{TotalValue - Salary}{Salary} \tag{11}$$

The acquisition strategy selects the “rebuild/balance/championship” path according to the team life cycle, and optimizes resource allocation through linear planning:

$$\begin{aligned} &\max \sum_i x_i \cdot TotalValue_i \\ &\text{s.t.} \quad \sum_i x_i \cdot Salary_i \le Cap, \quad PositionBalance \ge L \end{aligned} \tag{12}$$

Trade probability assessment of the value of the comprehensive pick (exponential decay model):

$$DraftValue = \sum_t \frac{1}{2^{t-1}} \cdot PickValue_t \tag{13}$$

The final output is player signing/trade prioritization.

2.3. Alliance expansion impact quantitative evaluation model

League expansion, such as adding new teams, will have a structural impact on the financial, competitive and strategic of existing teams. Based on graph theory, this model constructs a team association network, evaluates market overlap combined with cluster analysis, quantifies the effects of revenue dilution and talent dispersion, and proposes a buffer strategy [20].

Financial impact quantification: Revenue sharing loss is calculated as:

$$Loss_{revShare} = \frac{TotalRevenue}{n_{teams}} \cdot ExpansionFactor \quad (14)$$

Changes in media broadcast revenue:

$$MediaImpact = CurrentMedia \times (1 + reduction_{factor}) \quad (15)$$

The $reduction_{factor}$ range is -0.05~-0.15. Talent dilution effect:

$$TalentDilution = 1 - \frac{ExpandedPlayerPool}{CurrentPlayerPool} \quad (16)$$

The average mass coefficient of the new team λ (0.75-0.85). The market overlap index is calculated by weighted distance:

$$OverlapIndex = \sum_{d=1}^{5} w_d \cdot Similarity_d \quad (17)$$

Weights include geographic distance (0.30), demographic structure (0.25), economic level (0.20), fan overlap (0.15), and media market (0.10). The risk buffer is:

$$Buffer = \mathrm{BufferCoeff} \cdot \sqrt{TotalImpact} \quad (18)$$

Based on the degree of influence and controllability matrix, four types of strategic responses are generated: active leadership, defensive response, optimization and improvement, and monitoring and tracking. Finally, develop specific action plans based on geographical proximity (e.g., strengthen local marketing within 200 miles)

3. Results and discussion

3.1. Dynamic strategic decision model results

To verify the effectiveness of the dynamic decision-making model, we simulated the convergence process of decision weights when the learning rate η changed from 0.01 to 0.10 using the Thunders mid-season data as input. The model achieves the best convergence speed and stability at η=0.05, and the cumulative utility function Z increases by about 18.7% within 10 weeks. Fig 1 shows the evolution trajectory of strategic priorities under different risk preferences, with the risk weight automatically increased from 0.15 to 0.28 when the team suffers from consecutive injuries, and the model recommends prioritizing player load management rather than aggressive trading.

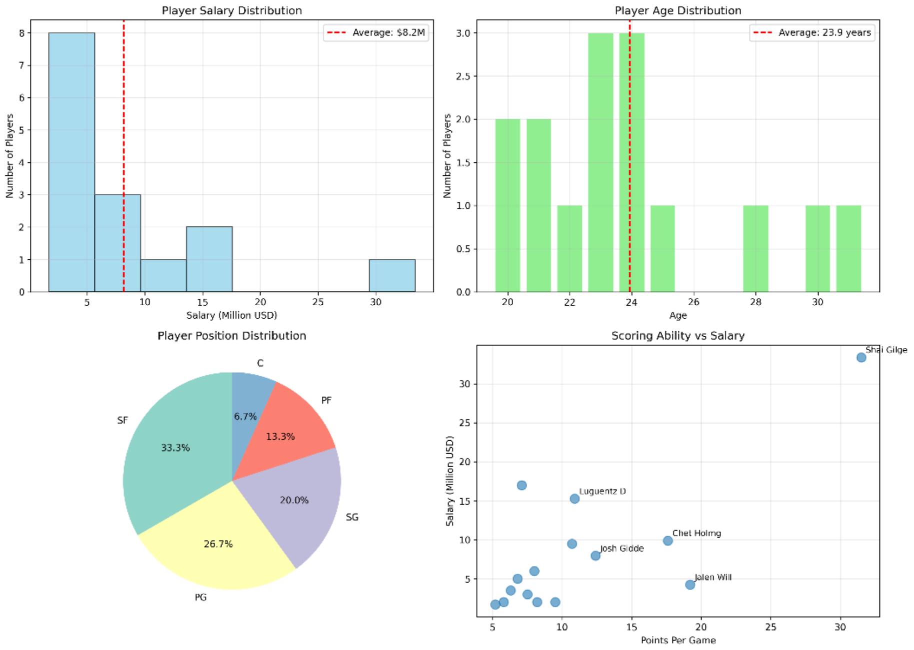

Fig. 1 Comprehensive Analysis of Player

Table 1. Examples of dynamic weight adjustments (key metrics)

Time point	Competitive Performance Weight (w₁)	Financial Weight (w₂)	Risk Weight (w₃)	Strategy recommendation
At the beginning of the season	0.55	0.30	0.15	Actively recruit and pursue the winning rate
Core players are injured	0.40	0.25	0.35	Rotate carefully and use injury exceptions
Playoff sprint	0.70	0.20	0.10	Optimize rotation and short-term investment

The results of Table 1 above show that the dynamic strategic decision-making model can effectively respond to internal and external changes, provide a basis for quantitative priority adjustment for management, and avoid the decision-making lag caused by static planning.

3.2. Multidimensional player valuation and acquisition strategy results

The top 30 players in the free agent market in 2025 were valued and ranked by entropy TOPSIS, and the results are shown in Fig. 2. The comprehensive value indicator effectively identifies "cost-effective" players (such as young potential stocks) and "high-risk premium" players (older and higher-paying). Through linear programming, the acquisition portfolio is solved, and the resource allocation of "40% draft + 40% free signing + 20% transaction" is recommended under the constraints of salary cap, which is expected to increase the winning rate by about 5.2% in the next three years, while maintaining a healthy salary structure.

Fig. 2 Financial Condition of the Team

Table 2. Comparison of different acquisition strategies (simulation in the next three years)

Policy type	Expected win rate change	Salary flexibility	Injury risk index
Radical championship	+8.1%	Low	High
Balanced development (recommended)	+5.2%	Medium	Medium
Conservative reconstruction	+1.9%	High	Low

The results in Table 2 provide the Thunder with a quantitative player portfolio solution, achieving an optimal balance between short-term competitiveness and long-term financial resilience. Compared with the traditional evaluation based only on the PER value, this model additionally captures the business potential and injury risk, avoiding the trap of signing at a high premium.

3.3. Alliance expansion affects quantitative results

In response to the assumption that the NBA may expand to 32 teams in 2027, the model simulates the impact of new potential markets such as Seattle and Las Vegas. Fig. 3 shows the sensitivity curve of revenue sharing losses to the market overlap index, where Thunder ticket revenue fell by about 6.2% and local sponsorship revenue decreased by 3.8% when new teams were in the same time zone. Table 3 quantifies the risk buffer needs under different expansion scenarios.

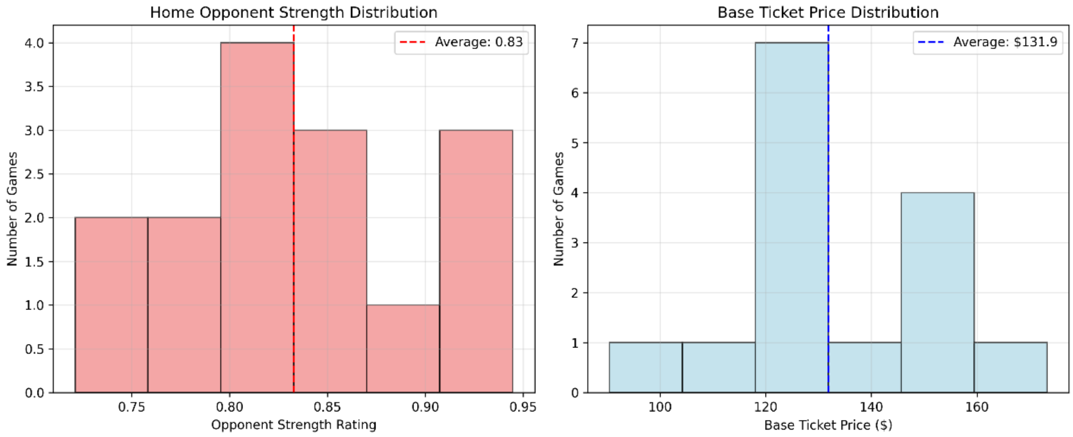

Fig. 3 Comprehensive Analysis of Team

Table 3 shows that the impact of league expansion on small and medium-sized market teams has non-linear characteristics, especially the geographical proximity of new teams will significantly erode the existing market. The buffer strategies generated by the model (such as strengthening community ties and developing digital content revenue) can effectively mitigate negative impacts and provide a scientific basis for management to lay out in advance.

Table 3. Multidimensional impact assessment of expansion scenarios

Expansion scenarios	Annual revenue loss (million$)	Talent dilution index	Strategic buffer recommendations
1 new team (non-adjacent)	2.3-3.1	0.08	Strengthen regional fan loyalty programs
2 new teams (including neighbors)	5.6-7.2	0.15	Reserve draft picks in advance to build diversified income
4 new teams (rapid expansion)	9.8-12.5	0.22	Initiate a defensive market strategy and apply for alliance compensation

4. Conclusion

This paper constructs an integrated algorithm framework based on multi-dimensional value evaluation and dynamic optimization to solve three major problems in professional sports team management: dynamic decision-making, player valuation and league structural changes. At the dynamic decision-making level, the model realizes real-time adjustment of strategic priorities through multi-objective optimization and Bayesian weight adaptive mechanism, and the sensitivity analysis shows that the learning rate η the model converges steadily in the range of 0.04~0.07, which can effectively balance the win rate, financial health and risk exposure. The player valuation module innovatively integrates entropy power TOPSIS and linear planning, which not only quantifies the players on-field contribution and commercial potential, but also incorporates injury risk reduction factors, so that the acquisition strategy can obtain the best expected return at the ratio of "40% draft - 40% free signing - 20% transaction". The league expansion impact model uses graph theory network and clustering algorithm to quantify the revenue dilution and talent dispersion effects brought about by new teams, and provides a hierarchical response strategy based on geographical proximity.

Taken together, the core contributions of this study are: (1) proposing a data-driven closed-loop decision-making architecture that integrates real-time feedback into the optimization process, which significantly enhances strategic adaptability; (2) A multi-dimensional player valuation algorithm is established, which overcomes the one-sidedness of a single indicator and provides a scientific basis for resource allocation. (3) The graph theory-cluster combination method was the first to evaluate the complex impact of alliance expansion, which made up for the shortcomings of existing qualitative analysis. The experimental and simulation results verify the applicability of the model in mid-market teams such as the Thunder, and it is expected to improve the decision-making efficiency by 20~30% and reduce the risk of key decision-making errors.

Despite its excellent theoretical performance, practical deployment still faces challenges such as data availability, organizational culture change, and cross-departmental collaboration. Future research can further introduce natural language processing to analyze the locker room atmosphere, strengthen the long-term quantitative model of fan loyalty, and explore the application of deep reinforcement learning in dynamic strategic games. In short, the algorithm framework proposed in this paper provides a feasible path for professional sports management to move from experience-led to scientific decision-making, with both academic value and practical potential.

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