Multi-Factor Evaluation of Performance and Momentum Prediction Models in Tennis Matches

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Abstract. With the increasing popularity and competitive nature of tennis, there is a growing demand for comprehensive analytical methods that can evaluate player performance and predict momentum shifts during matches. Traditional statistical approaches focus mainly on the result of the game, but they often fail to capture the complex dynamics that influence player performance throughout a game. In response to this need, our study proposes an integrated approach that combines the Analytic Hierarchy Process (AHP) and the Seasonal AutoRegressive Integrated Moving Average with exogenous factors (SARIMAX) model to comprehensively evaluate player performance and predict momentum. The AHP model considers critical factors such as won sets, won games, fatigue, and winning streaks, while the SARIMAX model is used to predict momentum changes based on match data. Our findings demonstrate a significant positive correlation between momentum and player performance, suggesting that momentum shifts can strongly influence the outcome of tennis matches. It also provides valuable insights into the dynamics of tennis performance and offers practical strategies for enhancing player performance through momentum analysis.

Keywords: Performance Indicators, AHP, SARIMAX, GARCH, Stepwise Regression.

1. Introduction

With the widespread popularity and ongoing development of tennis as a global sport, analyzing and predicting the performance of tennis players has become increasingly important. Traditional methods for analyzing match results primarily rely on overt data such as player scores, wins, and losses. However, these approaches often fail to capture the intricate factors and dynamic changes that occur throughout a match. A comprehensive analytical method is needed, one that takes into account multiple factors influencing player performance and effectively predicts momentum shifts during a game. Understanding these shifts in momentum is critical, as they can significantly impact match outcomes and provide valuable insights for players and coaches to optimize their strategies.

To address these challenges, our study employs two key analytical tools: the Analytic Hierarchy Process (AHP) and the Seasonal AutoRegressive Integrated Moving Average with exogenous factors (SARIMAX) model[1][2]. The AHP, introduced by Thomas Saaty, is widely used in decision-making processes to evaluate and prioritize complex factors through pairwise comparisons. In this research, this study applied AHP to assess multiple performance factors, such as won sets, won games, fatigue levels, and winning streaks, which are critical in evaluating a player's overall performance in a match. Furthermore, the SARIMAX model, a time-series forecasting method commonly used in financial and econometric studies, was implemented to predict momentum changes in tennis matches. The SARIMAX model's ability to incorporate external factors, such as player fatigue or match conditions, makes it particularly suitable for analyzing the fluctuating nature of momentum in sports competitions.

In this work, a comprehensive performance index for tennis players is first constructed using the AHP model. The SARIMAX model is then applied to analyze the relationship between momentum and player performance, predicting momentum shifts based on various in-game factors. Our study demonstrates that momentum has a statistically significant impact on player performance, and the integration of AHP and SARIMAX provides a robust framework for both performance evaluation and momentum prediction in competitive sports.

2. Analysis of Performance Factors in Tennis Matches

2.1. The Factors of Performance

To comprehensively evaluate a tennis player's performance, several key factors must be considered. Each of these factors contributes to the overall outcome of the match and helps in understanding the dynamics of the players' behavior[3]. Below, the critical factors are chosen for this study and provide reasons for their selection:

1. Won Sets: The number of won sets is a direct determinant of the match outcome. The player with more won sets is closer to victory, making this one of the most significant factors in assessing player performance. It directly affects the psychological state of both players, as more sets won provide a clear advantage.

2. Won Games: Similarly, the number of won games is crucial and closely related to won sets. The players' psychological state fluctuates with the changing number of won games, which indirectly influences the final match outcome by determining the number of won sets.

3. Fatigue Level: Fatigue is an essential factor in any sporting event. As the match progresses, players may experience decreased movement speed and reduced precision. Players with superior endurance are more likely to gain an advantage, particularly in longer matches, where stamina becomes a decisive factor.

4. Winning Streak: A winning streak can instill confidence in a player, allowing them to dictate the match's tempo. However, it can also potentially lower a player's vigilance, making it a double-edged sword in terms of performance.

5. Server: In tennis, the server often has a distinct advantage, with opportunities to score directly through aces. However, there is also the risk of losing points through double faults. The outcome of serves significantly impacts the player's mentality and subsequent performance during the match.

6. Won Points: Though less impactful than won games, every point in tennis is critical. Winning individual points can have a significant psychological effect and play a pivotal role in determining the direction of the match.

This detailed breakdown of factors provides a foundation for constructing a robust performance evaluation model. Each factor influences the outcome of the match in different ways, and understanding their interaction is key to accurate performance assessment.

2.2. The Establishment of the AHP Model

The data for this study was selected from 2023-wimbledon-1301 matches at “www.comap.com”:

In the beginning, the value of different factors of performance are set with the method of AHP. Specifically, the "server" is highly focused due to the saying in tennis, that the player serving has a much higher probability of winning the point/game.

This study sets the relative values of the six factors to different positive integers ranging from 1 to 6 based on the importance of the relevant factors, as shown in Table 1, and rank the six factors in importance according to our understanding[4]. The order of importance, from high to low, is Won Sets, Won Games, Fatigue Level, Winning Streak, Server, and Won points. Here are the reasons[5]:

1. For the won sets directly to determine the result of the match, it is put in the first position.

2. For the won games it indirectly determines the result of the match and is also an essential part of the match, it is put in the second position.

3. For the fatigue level can influence the physical and mental status of players, it is put in the third position.

4. For the winning streak is closely related to the mental status of players, it is put in the fourth position.

5. For the server has a clear advantage while it might lose points with double fault, it is put in the fifth position.

6. For the won points can measure the short-term performance of players, it is put in the sixth position.

Table 1: Allocation of Weights

	Won Sets	Won Games	Fatigue Level	Winning Streak	Server	Won points
Won Sets	1	2	3	4	5	6
Won Games	1/2	1	2	3	4	5
Fatigue Level	1/3	1/2	1	2	3	4
Winning Streak	1/4	1/3	1/2	1	2	3
Server	1/5	1/4	1/3	1/2	1	2
Won points	1/6	1/5	1/4	1/3	1/2	1

As a result, the Pairwise Comparison Matrix W (The Pairwise Comparison Matrix of weights) is built:

$$W = \begin{pmatrix} 1 & 2 & 3 & 4 & 5 & 6 \\ 1/2 & 1 & 2 & 3 & 4 & 5 \\ 1/3 & 1/2 & 1 & 2 & 3 & 4 \\ 1/4 & 1/3 & 1/2 & 1 & 2 & 3 \\ 1/5 & 1/4 & 1/3 & 1/2 & 1 & 2 \\ 1/6 & 1/5 & 1/4 & 1/3 & 1/2 & 1 \end{pmatrix} \tag{1}$$

The matrix can pass the consistency test, and the weight vector obtained by the Eigenvalue Method is:

$$w = [0.38249747, 0.25040175, 0.15958026, 0.10063029, 0.0640774, 0.04281282] \tag{2}$$

The performance of players is measured by performance index p_1 and p_2. For p_i(i=1,2), the “The Factors of Performance” are applied to the count of it. Let $w_{i,j}$ and $v_{i,j}$ be the weights and value of the factor of j of player i. The performance index for player i is given by:

$$p_i = \sum_{j=1}^{6} w_{i,j} v_{i,j} \tag{3}$$

Let P stands for the performance difference between players and I stand for the number of players, The performance difference can be expressed as :

$$P = p_1 - p_2 \tag{4}$$

For other matches, same method can also be used to develop the corresponding model according to the given data.

2.3. Data Visualization

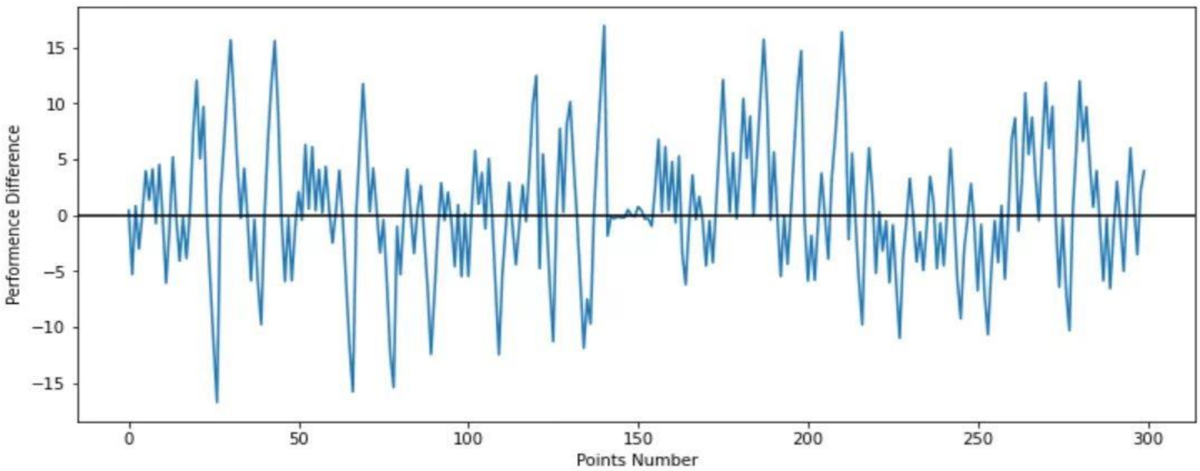


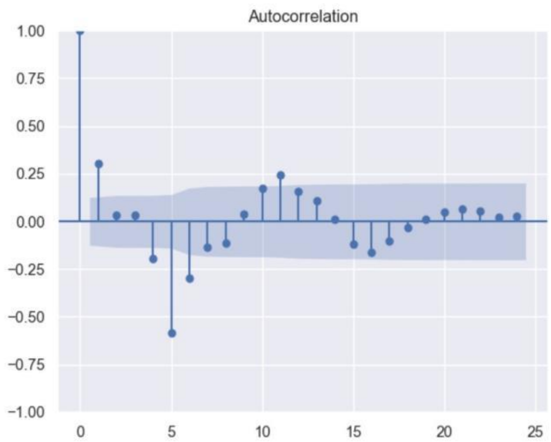
Figure 1: The Performance Result of 2023-wimbledon-1301

The data is transformed into representations and visualized through Figure 1. The relative performance of players can be measured by performance difference. From a qualitative perspective, the performance of players can be compared by the positive or negative of the performance difference. When the performance difference is greater than 0, it means that player 1 performs better, and conversely, it means that player 2 has better performance. Specifically, when the performance difference is 0, the performance of the two contestants is equal and there is no distinction between superiority and inferiority. From a quantitative perspective, the distance between the performance difference and the horizontal axis of the coordinate axis indicates the difference between the two players. That is to say, the larger the absolute value of performance difference is, the greater the difference in performance among players.

3. Time Series Analysis of Tennis Momentum Using SARIMAX

3.1. The Establishment of the SARIMAX Model

Given the known positive correlation between momentum and performance, changes in momentum can be detected to predict the trend of the match. After autocorrelation detection, it is known that the momentum is autocorrelated on the time scale, which gives us the opportunity to use SARIMAX[6].



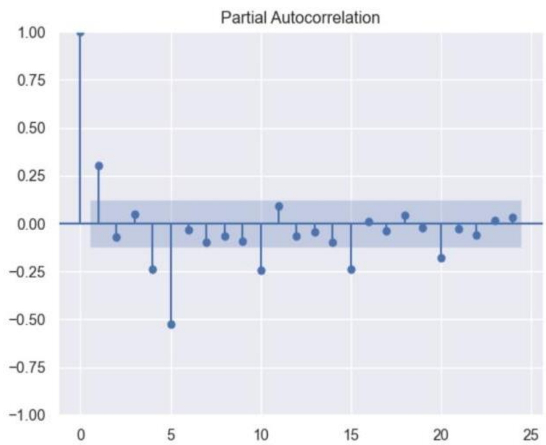


Figure 2: The Autocorrection Detection

When conducting time series analysis, if differential processing is not performed, the sequence often exhibits instability. After first-order differential processing, the sequence becomes stationary. To test the autocorrelation of the sequence, the study used the Ljung Box Q test and found that the p-value of the sequence was extremely small, which means that the sequence passed the white noise test, indicating a certain degree of autocorrelation in the sequence[7]. Based on these findings, the SARIMAX model was chose to use to model time series.

The SARIMAX Model wants to express it as a multiply form.

$$ARIMA(p,d,q) \times (P,D,Q)_m \tag{5}$$

Where s stands for seasons, means that the seasonal effect was considered. The data process can be written as:

$$\varphi_p(L)\tilde{\varphi}_P(L^m)y_t^* = A(t) + \theta_q(L)\tilde{\theta}_Q(L^m)\varepsilon_t \tag{6}$$

In the selection of model parameters, the optimal model parameters were obtained by applying the Akechi Information Criterion (AIC). P=3, d=1, q=3, P=1, D=0, Q=0, m=4.

In this model, the p-values for the variables **server win** and **win shot** are significantly less than 0.05, indicating that these variables have a significant impact on momentum. Predictions were made based on selected parameters for a portion of the data.

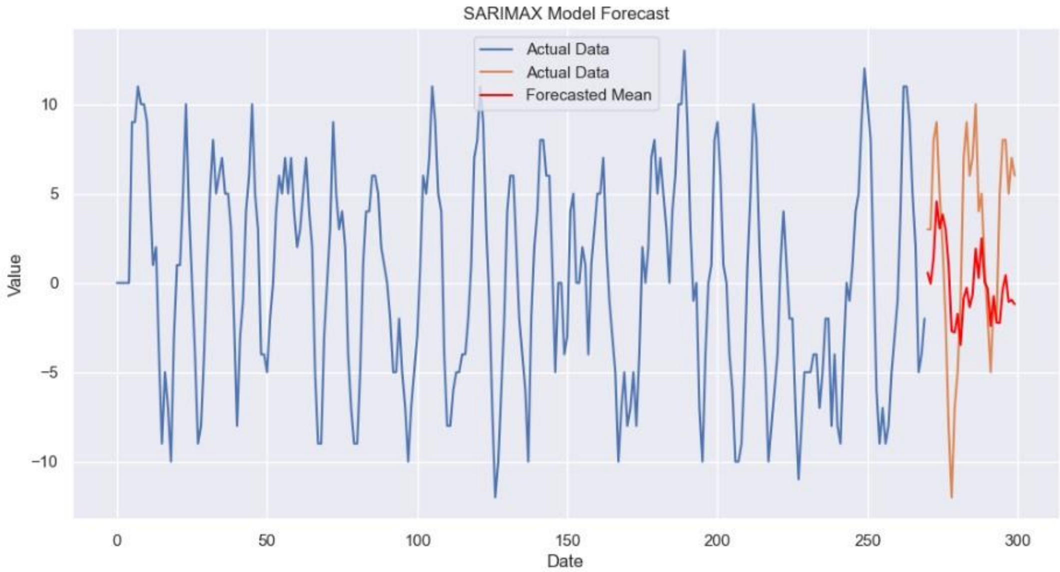


Figure 3: Momentum Forecast

However, while the SARIMAX model offers certain insights, its outcomes might not be entirely satisfactory[8]. Therefore, this study utilized the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to forecast the volatility of momentum changes[9]. By integrating the predictive outputs of the SARIMAX model with the volatility forecasts from the GARCH model, it was able to derive more accurate predictions of momentum changes[10]. This approach enables us to more comprehensively capture the complexities and volatilities affecting the game's momentum, thereby providing a more detailed and accurate forecasting technique.

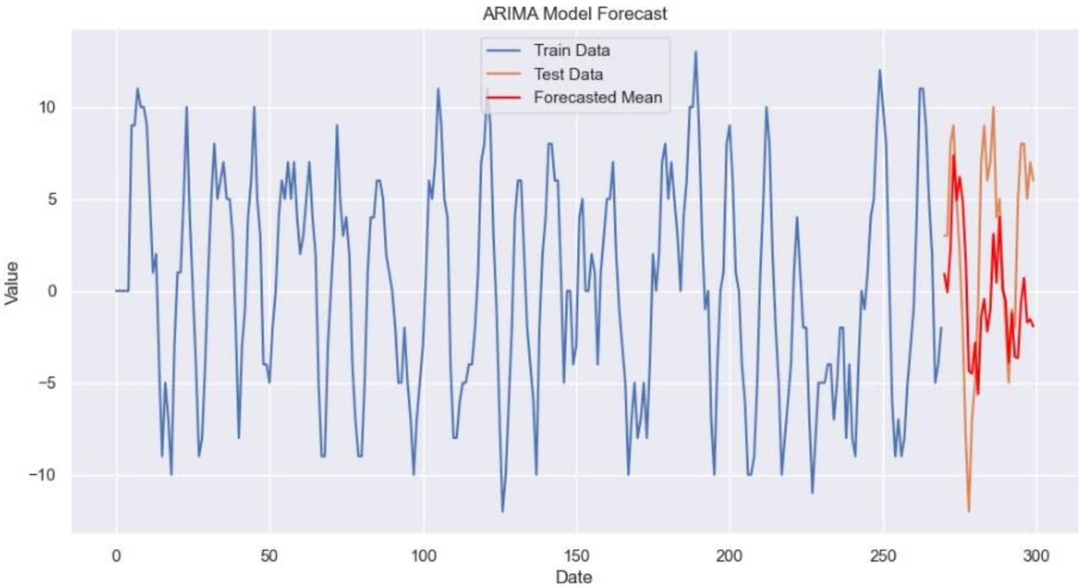


Figure 4: Momentum Forecast (After Improvement)

By combining the SARIMAX model with the GARCH model, the accuracy and stability of the predictions were significantly enhanced. Originally, SARIMAX provided a relatively clear framework for momentum changes by capturing the seasonality, trend, and autoregressive characteristics of the time series. However, this framework failed to fully address the complex and dynamic fluctuations in the game, especially when sudden events or short-term volatility occurred, leading to suboptimal predictions. The introduction of the GARCH model brought a qualitative improvement to the forecasting capability. The core advantage of GARCH lies in its modeling of volatility, enabling the model to capture the uncertainty and fluctuations in momentum changes, thus making the prediction of momentum movements more precise. This improvement means that the forecast is no longer limited to long-term trends but becomes more sensitive to instantaneous fluctuations, particularly during critical moments, where the model can capture and alert on sharp momentum shifts.

4. Conclusions

This study presents a comprehensive framework for evaluating tennis player performance and predicting momentum shifts during matches. First, a performance assessment model using the AHP was developed, considering key factors such as won sets, won games, fatigue level, and winning streak to create a comprehensive performance index. This index effectively quantified and visualized the differences in players' performance throughout the match. In addition, it employed the SARIMAX model to predict momentum changes, demonstrating a strong positive correlation between momentum and player performance. Critical moments, such as server wins and winning shots, were identified as having a significant influence on momentum, offering a clear understanding of player behavior during crucial phases of the match.

This study provides a robust research framework for sports performance analysis, illustrating the feasibility of combining AHP and SARIMAX models to evaluate dynamic processes like momentum changes in tennis. By integrating these models, this study provides a practical approach to addressing the challenges of performance evaluation and momentum prediction in competitive sports. Future research may refine this approach and explore its adaptability to various competitive scenarios, reinforcing its value in sports analytics.

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