Research in Physical Education, Sport and Health
2024, Vol. 13, No. 1, pp.21-27
ISSN(Print):1857-8152; ISSN(Online):1857-8160

WORKLOAD RATIO ASSESSMENT IN FOOTBALL: EVALUATING SIMPLE AND EXPONENTIAL MOVING AVERAGES

DOI: https://doi.org/10.46733/PESH24131021v
(Original scientific paper)

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Abstract

Introduction: To identify the optimal technique for examining time series data related to the Acute Chronic Workload Ratio (ACWR), correlations between the Simple Moving Average (SMA) and the Exponentially Weighted Moving Average (EWMA) were investigated in this study utilising a decay factor (λ) over a period of 7/28 days. Five GPS metrics were included in our analysis: Total Distance, Accelerations, Decelerations, High Metabolic Load Distance, and Distance in Speed Zones 3+4+5 (>19,9 km/h). These data points were collected from 22 players across 47 days, excluding the first 28 days, for a total of 596 data points per pair [SMA/EWMA].Methods: Shapiro-Wilk and Kolmogorov-Smirnov normality tests were performed on the SMA and EWMA datasets prior to using the Spearman, Kendall Tau, and Distance Correlation techniques to assess correlations and dependencies between pairings. Using Python and libraries including Pandas, NumPy, Matplotlib, SciPy, Scikit-Learn, Statsmodels, OpenPyXL, Dcor, and IPython.display, the analysis was carried out in Anaconda's Jupyter Notebook.Results and Discussion: Significant departures from the normal distribution were shown by normality tests (p<0.05 for most of the variables). With p-values of 0.00, Spearman analysis showed significant correlations for every pair of variables, ranging from moderate (0.46) to somewhat weak (0.23). Additionally, Kendall's Tau revealed statistically significant correlations (p=0.00) across strengths, ranging from moderate (0.32) to weak (0.16). With values ranging from 0.25 to 0.44, Distance Correlation showed significant connections (p<0.00), while Energy Distance values displayed a range of discrepancies. Interestingly, EWMA frequently displayed values that were marginally lower than SMA, highlighting a significance level of p=0.00.Conclusion: The results show continuous trends and modest to moderate positive correlations between the variables under study. Both SMA and EWMA can be used with the help of distance correlation. EWMA is typically chosen for responsive trend analysis and offering a realistic representation of current conditions in ACWR monitoring due to its emphasis on recent data. The decision between SMA and EWMA, however, may change depending on the coaching needs; in this study, EWMA approaches produced somewhat lower scores than SMA.

Keywords*: Training Workload; Professional Football; GPS Monitoring; Training Load Metrics; Time Series Analysis.*

Introduction

For coaches, managing training load properly is still a difficult undertaking that requires careful task optimisation. Wearable GPS trackers measure a variety of physical parameters to give a thorough picture of training and match loads. Coaches must be able to analyse this data, make inferences, and give the coaching team constructive criticism and direction. Calculated metrics, like the Acute Chronic Workload Ratio (ACWR), provide a summary of trends within data series for several metrics in addition to using raw data (Murray, N. B., et al, 2017; Springham, M., et all 2020). According to Gabbett, T. J. (2016), precisely calculating training load, including acute and chronic workload ratios, is a way to anticipate and stop injuries associated to training, which eventually improves players performance.

An athlete's risk of injury can be evaluated by comparing their recent training load to their long-term training load using the Acute Chronic Workload Ratio (ACWR) (Bowen, L., 2017). By analysing variations in workload over these time intervals, ACWR helps athletes monitor and control their risk of injury by providing a ratio of their training load over a recent 7-day period (acute) to their training load over a longer 28-day period (chronic) (Gryphon, A., et al, 2020).

Smoothing is a technique that highlights longer-term trends in data and minimises short-term variations by using moving (rolling) averages (Oliva-Lozano et al., 2021). According to Gabbett, T. J., et al. (2019), there are two basic approaches for determining ACWR: the coupled technique, in which the latest seven days coincide with the 28-day period, and the uncoupled method, in which the acute workload (seven days) is subtracted from the chronic workload calculation, which takes three weeks to complete. This investigation used a linked technique.

Some studies highlight the drawbacks of using ACWR directly (Menaspà, P., 2017), particularly its incapacity to take into consideration fluctuations that occur within the predetermined time frame and its disregard for the timing of training stimuli. Crucially, a stimulus's effect fades over time. However, contrasting acute with chronic workload A negative training-stress balance, where acute workload is greater than chronic workload, was shown by Hulin, B.T., et al. (2014) and was linked to a higher risk of injury in the following week. Weightlifting (Coyne, J. O., et al., 2020), basketball (Coyne, J. O., et al., 2021), rugby (Hulin, B. T., et al., 2016), volleyball (Timoteo, T.F., et al., 2016), cricket (Hulin, B. T., et al., 2014), etc. are only a few sports where ACWR approaches are employed.

Two main moving average types are used in sports analytics, mainly for workload management and forecasting: Simple Moving Average (SMA) and Exponential Weighted Moving Average (EWMA). These methods are increasingly being utilised in sports to reduce data oscillations. They are frequently employed in financial forecasting (Fernando, J., 2023) for stock forecasts. This mathematical smoothing is particularly helpful in sports like football where accurate performance analysis is crucial since it helps provide a clearer image of the data trends over time.

A smoothed picture of the data trend is produced by the Simple Moving Average (SMA), which computes the average of a predetermined number of data points over a given time period (7 vs. 28 days, for example) (Bowen, L., 2017). By assigning exponentially decreasing weights [decaying exponential factor - λ] to historical data points, the Exponential Weighted Moving Average (EWMA) prioritises recent observations and makes it possible to identify trends and changes more quickly (Williams, S., et al., 2017, Lazarus, B. H., et al (2017).

The effectiveness of SMA versus EWMA smoothing techniques is still a little bit ambiguous. By utilising GPS measures, this study aims to fill the knowledge gap regarding the relationship between both techniques (SMA vs. EWMA) for football training and match load assessments. Most published studies have been on determining ACWR using TRIMP (Arazi, H., 2020) or RPE (Bowen, L., 2017). It has also been used to incorporate football GPS measurements (Bowen, L., 2017; Jaspers, A., et al., 2018). By including external load measurements unique to football and examining connections between the Simple Moving Average (SMA) and the Exponential Weighted Moving Average (EWMA), our study goes beyond earlier studies in this area. The purpose of this study is to examine how SMA and EWMA smoothing techniques relate to one another when evaluating football training and match loads using GPS measurements. Our aim is to ascertain whether there exists a noteworthy distinction between the two methods when it comes to calculating load measures in football. Based on previous studies that evaluated ACWR in football using the TRIMP and RPE techniques, we predict that SMA and EWMA will both show a strong relationship with football-specific external load measurements. We forecast that EWMA would show somewhat higher values than SMA, suggesting a greater focus on recent data points when evaluating workload.

Material & methods

GPS trackers were used to track the external training loads of 22 professional football players from the Bulgarian football league system's top division, the First Professional Football League (Barin). The following metrics were noted: Total Distance (TD), Accelerations (ACC), Decelerations (DEC), High Metabolic Load Distance (HMLD), and Distance in Speed Zones 3+4+5 (DZ345). Seventy-five training sessions and games were observed. However, because Simple Moving Averages were not consistently calculated over the first 28 days, their data were not included. Therefore, data from 47 training sessions and/or matches are included in the analysis conducted in this study. The training sessions were a component of the competitive microcycles and fundamental preparations. Power BI was used to construct the ACWR visualisation graphs (Scan QR code- Figure 1- for Power BI model visualisation). Power BI measures (functions like compute, SUM, DATESINPERIOD, and LASTDATE were used to compute acute (7 days) and chronic (28 days) loads) were used to determine the SMA for each metric. Acute and chronic loads were divided to determine ACWR. An R script that was run within Power BI was used to calculate the ACWR by EWMA. Using the pracma package, this script computed the exponential moving average with the default decay factor λ=n+12, as stated by Borchers (2024). The number of periods, or n in this case, is 28. The results were printed as columns for each measure, player, and date point in the EWMA's ratio analysis. These outcomes were combined in Power BI using the AVERAGE measure, and then they were exported to a CSV file. The dataset included 596 data points in total for every pair of GPS parameters that were subjected to both EWMA and SMA (Simple Moving Average) analyses.

Anaconda's Jupyter Notebook was used to run Python scripts for the statistical analysis. Numerous libraries and functions were used in the analysis: NumPy supported large arrays and mathematical functions; Matplotlib was used to create visualisations; and SciPy was used for statistical tests, such as the t-test between SMA and EWMA for each pair of metrics, skewness, kurtosis, Kendall Tau correlation, Shapiro-Wilk, and Kolmogorov-Smirnov. In addition, Statsmodels was used for testing, modelling, and data exploration, and DCOR was employed to calculate the distance correlation between numerical data arrays. To reading and writing Excel files, OpenPyXL was included. Complete project available at https://github.com/vucko77/SMA-vs-EWMA (codes and documentations).

Figure 1: QR Code for accessing data visualization.

Results

The Shapiro-Wilk test (Table 1) shows that most variables in the SMA and EWMA series have significant deviations from normality ($p < 0.05$), apart from TD_EWMA ($p = 0.25$) and HMLD_EWMA ($p = 0.13$), both of which have a Shapiro-Wilk value of 1, suggesting normality ($p > 0.05$). Similarly, for five metrics (DZ345_SMA, HMLD_SMA, TD_SMA, ACC_EWMA, and DEC_EWMA), the Kolmogorov-Smirnov test supports these findings with significant deviations ($p<0.05$). The exceptions are DZ345_EWMA, HMLD_EWMA, TD_EWMA, ACC_SMA, and DEC_SMA, where the KS statistic ranges between 0.04 and 0.05, indicating normal distribution ($p>0.05$).

Table 1: Statistical Tests for Assessing the Normality of Data Variables.

Column Name	Shapiro Stat	Shapiro P-value	KS Stat	KS P-value	Skewness	Kurtosis
DZ345_EWMA	0.99	0.00	0.04	0.40	0.34	-0.02
DZ345_SMA	0.94	0.00	0.10	0.00	1.14	2.87
HMLD_EWMA	1.00	0.13	0.04	0.38	0.19	0.07
HMLD_SMA	0.96	0.00	0.08	0.00	0.77	2.17
TD_EWMA	1.00	0.25	0.04	0.44	0.02	-0.01
TD_SMA	0.96	0.00	0.08	0.00	0.77	2.17
ACC_EWMA	0.99	0.00	0.06	0.02	-0.27	0.76
ACC_SMA	0.99	0.00	0.05	0.16	0.25	0.67
DEC_EWMA	0.98	0.00	0.06	0.049	-0.45	0.88
DEC_SMA	0.99	0.00	0.05	0.11	0.30	0.76

Three correlation tests—Spearman, Kendall Tau, and Distance Correlation—were used to investigate the similarities between the SMA and EWMA ratios for Acute Chronic Workload, given the results showing non-normal distribution of most of the variables (Table 2). With significant p-values (0.00), the Spearman Correlation, a non-parametric metric, evaluates links based on ranking values and finds moderate to weak correlations between SMA/EWMA pairs. The strongest link is shown by DZ345_SMA / DZ345_EWMA (r_s=0.46), while the lowest link is shown by DEC_SMA / DEC_EWMA (r_s=0.23). The variation in correlation strength indicates that there may be variations in the sensitivity to data modifications or smoothing effects among the pairs. In a similar vein, Kendall Tau, which provides better interpretability and robustness to outliers, showed that DZ345_SMA and DZ345_EWMA had the largest correlation (τ=0.32), while DEC_SMA and DEC_EWMA had the weakest (τ=0.16τ=0.16), both of which were significant. These weak to moderate correlations imply varying degrees of reliance, which could be the result of various processing reactions to the underlying measures. In addition, Distance Correlation, which measures linear and non-linear relationships, revealed that DZ345_SMA and DZ345_EWMA have the highest link (R=0.44), while DEC_SMA and DEC_EWMA have the smallest (R=0.25). All these relationships are statistically significant (p-value = 0.00). These results reinforce different levels of dependency with Energy Distances ranging from 0.03 to 0.08, emphasising the dynamic behaviours and complexity in the data sets. The observed trends are further reinforced by the 95% confidence intervals for the correlation coefficients across the SMA/EWMA pairs, which further confirm these findings: While DEC_SMA / DEC_EWMA has the narrowest interval from 0.16 to 0.31, consistent with its weakest correlation, DZ345_SMA / DZ345_EWMA shows the largest interval range from 0.40 to 0.52, confirming its significant connection. These intervals demonstrate the robustness of the correlations and underline the variety in association strength among the couples.

Table 2: Correlation Metrics and Confidence Intervals for SMA/EWMA Pairs Across Different Tests.

		Spearman		Kendall Tau		Distance Correlation			95% Confidence	
SMA / EWMA Pair	**N**	**r_s [rho]**	**p-value**	**τ coeff.**	**p-value**	**R**	**p-value**	**Energy Distance**	**Interval Lower**	**Interval Upper**
DZ345_SMA / DZ345_EWMA	596	0.46	0.00	0.32	0.00	0.44	0.00	0.03	0.40	0.52
HMLD_SMA / HMLD_EWMA	596	0.30	0.00	0.21	0.00	0.29	0.00	0.04	0.22	0.37
TD_SMA / TD_EWMA	596	0.31	0.00	0.21	0.00	0.29	0.00	0.07	0.23	0.38
ACC_SMA / ACC_EWMA	596	0.29	0.00	0.20	0.00	0.28	0.00	0.08	0.21	0.36
DEC_SMA / DEC_EWMA	596	0.23	0.00	0.16	0.00	0.25	0.00	0.07	0.16	0.31

A quadratic polynomial curve fitted to the data points illustrates potential non-linear relationships, and color-coded markers clearly distinguish the two variables on the scatter plots (Figure 2) for each pair. One variable in each pair is vertically offset for improved visibility due to the significant overlap of the data.

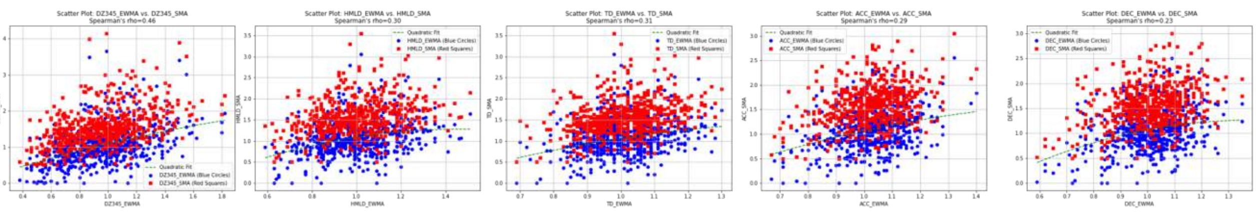

Figure 2: Scatter Plot of SMA/EWMA Pairs including Spearman r and quadratic polynomial curve.

The visualisations (Figure 1-QR code) clearly illustrate the differences between SMA and EWMA. The data points of the curves indicate that SMA occasionally registers greater values than EWMA and vice versa. Frequencies were computed (Table 3) to quantify these fluctuations by calculating the frequency at which SMA vs EWMA showed higher or lower values. 596 pairs of each SMA and EWMA metric combination were used in a paired t-test for dependent samples. At a p-value of 0.00, the findings showed statistically significant differences across all pairs of measurements (Table 3).

Table 3: Comparison of frequency counts where SMA exceeds EWMA across metrics, including t-test.

Metrics	SMA	EWMA	Net Difference (SMA-EWMA)	zeros counts	t-test	p-value
DZ345	308	281	27	6	4.35	0.00
HMLD	325	260	65	10	3.93	0.00
TD	309	282	27	4	3.10	0.00
ACC	340	249	91	6	3.88	0.00
DEC	322	265	57	8	3.34	0.00

Discussion

This study aims to investigate the relationship between Simple Moving Average (SMA) and Exponentially Weighted Moving Average (EWMA) smoothing techniques while assessing GPS readings for football training and match loads. With the exception of TD_EWMA and HMLD_EWMA, which reflect a normal distribution, the study's findings show considerable departures from normality for the majority of the variables in both the SMA and EWMA series. Moderate to weak correlations between SMA/EWMA pairs are found using Spearman, Kendall Tau, and Distance Correlation correlation analyses; significant p-values (0.00) indicate consistent patterns. The DZ345_SMA and DZ345_EWMA have the strongest association, whereas the DEC_SMA and DEC_EWMA have the weakest. These results imply that the pairs differ in their sensitivity to changes in the data or smoothing effects. Potential non-linear correlations are shown by fitting a quadratic polynomial curve to the data points; on scatter plots, the variables are distinguished by color-coded markers. The visualisations illustrate the distinctions between EWMA and SMA, using computed frequencies to measure fluctuations. Paired t-tests for dependent samples verify statistically significant differences across all measurement pairs. Overall, the findings highlight the complex and dynamic behaviours found in the data sets, offering understanding of the interplay between SMA and EWMA when evaluating football practice and game loads with GPS measurements.

The strength of the monotonic association is indicated by the Spearman rs values. The dataset's strongest relationship, with an rs of 0.46, indicates a moderately positive correlation, meaning that as one variable rises, the other likely to rise predictably but not significantly. On the other hand, a weak positive correlation with an rs of 0.23 (the weakest link) denotes a less steady or predictable rise between the variables. It is important to note that all Spearman rs values have p-values of 0.00. Regardless of how strong they are, it indicates that these relationships are statistically significant. The trustworthiness of the identified links is confirmed by the statistical significance, which suggests that the observed correlations are unlikely to be the result of random chance.

The strength and direction of the relationship between two ranking variables are measured by the Kendall Tau coefficient (τ). The dataset's greatest τ of 0.32 denotes a moderately positive correlation, meaning that as one variable rises, the other also likely to rise in a ranked fashion. Although it is moderate, this is the strongest association that has been found in the dataset, which could mean that even if the variables are related, many other factors may also have an independent effect on the behaviours of the variables. Conversely, a $\tau = 0.16$ indicates a less robust positive association. This suggests that there is a weaker and less consistent correlation between the variables. It implies that although the variables have a propensity to rise in tandem, the link is weak and unreliable. All results are statistically significant (p-values < 0.05), which suggests that the observed links are not likely the consequence of random chance, even though the strength of these correlations is quite low. This importance emphasises that there is a real relationship between the variables, albeit a weak one. It is crucial for directing choices or interpretations that depend on these interactions' dependability and consistency. In situations where precise prediction is less important than trend identification, even moderate correlations like τ=0.32 might be practically meaningful. This may be important in planning and forecasting, because understanding a relationship's broad trajectory is more important than accuracy predictions.

Any linear or non-linear relationship between two variables is measured by the Distance Correlation Coefficient (R). Regardless of how the variables are related (linear or non-linear), a result of R=0.44 shows the strongest correlation found in the dataset and points to a very reasonable association where the variables tend to change together. On the other hand, the lowest correlation, R=0.25, indicates a weaker but still noticeable association, indicating less consistency in the combined variability of the variables. The confidence in these results is greatly increased by the fact that all correlations—even the weakest—have a p-value of 0.00. It suggests that the correlations found are very unlikely to have happened by accident, confirming the validity of the connections that have been found.

To improve the clarity of each dataset's visualisation, the scatter plots for two pairs of data were altered along the y-axis to reflect the substantial correlations that were previously described. If not, these strong connections would cause the data points to overlap. However, the existence of weak and moderate correlations frequently highlights the complex dynamics of the variables at play, where results are usually influenced by multiple factors. This intricacy ought to stimulate additional research, potentially utilising sophisticated analytical techniques as machine learning models or Bayesian Modified-EWMA (Aslam, M., & Anwar, S. M., 2020).

According to Coyne, J. O. (2021), this finding supports the idea that more research is needed to determine which moving average—the SMA or the EWMA - has a stronger correlation with training load and performance indicators. Although there are no direct comparisons between the SMA and the EWMA in football-related sports analytics, Fernando, J. (2023) points out that the correlations that are detected are in close agreement with stock evaluations. This points to a bright future for integrating these approaches into several domains.

This study provides insightful information on how SMA and EWMA interact in professional football settings to assess Acute Chronic Workload Ratios (ACWR) using GPS measurements. Nonetheless, several restrictions and directions for additional research deserve attention. First off, the study's small sample size of 22 players from one league limits how broadly its conclusions can be applied. This emphasises the need for larger, more varied samples that include players from other leagues and levels of competition. A more comprehensive understanding of workload dynamics and injury prediction can be achieved by incorporating additional measurements, such as subjective wellness scores and heart rate variability, as highlighted by the focus on a small collection of GPS parameters. Investigating cutting-edge analytical strategies, such as machine learning algorithms, may reveal complex workload patterns that are missed by conventional statistical tools. Refining workload management strategies requires going beyond 47 days for data gathering and looking at the practical implications of SMA and EWMA results for coaches and practitioners. Prospective directions for future research include comparative analyses comparing SMA and EWMA with alternative methodologies to workload measurement and long-term studies that monitor the workload profiles of athletes over several seasons. Conclusively, the evaluation of the feasibility and efficacy of utilising SMA and EWMA-based workload monitoring systems in real football environments is crucial in translating research outcomes into operational protocols. Evidence-based policies for workload management and injury prevention in football contexts will evolve if highlighted deficiencies are addressed and new research initiatives are explored, even if this study increases our understanding of SMA and EWMA methodologies in ACWR analysis.

The results of this study have important ramifications for how workload management techniques are used in professional football environments. Through a thorough understanding of the differences between SMA and EWMA in the context of GPS metrics analysis for ACWR, coaches and practitioners can better tailor training plans to reduce the risk of injury and improve performance outcomes. Tailored therapies can be adopted for individual players by integrating the insights gained from this research, such as the identification of workload patterns related with injury vulnerability. Furthermore, based on the unique context and workload analysis goals, the comparison of the SMA and EWMA approaches provides helpful advice on which technique is best. Through the integration of sophisticated analytical methods, such machine learning algorithms, coaches can enhance their comprehension of workload dynamics and customise interventions to cater to players' changing requirements. Utilising the results of this study ultimately promotes a more methodical and proactive approach to injury prevention and performance optimisation in professional football situations by facilitating evidence-based decision-making in workload management.

Conclusions

The results of this study showed a substantial association for the metrics under study between the Simple Moving Average (SMA) and the Exponential Weighted Moving Average (EWMA). It is not surprising that the two measurements have a link because they are moving average derivatives. Though there is a correlation, the approaches cannot be used interchangeably. By giving equal weight to all data points, the SMA produces a smoother line, whereas the EWMA, by emphasising recent data more, produces a more responsive indicator (Fernando, 223).

The EWMA may be more beneficial in real-world applications like coaching, where adaptability to recent changes can be critical, as suggested by Murray, N. B., et al. (2017) and Gryphon, A., et al. (2020). This is especially important to take into account when looking at the acute:chronic workload ratio (ACWR), as the EWMA (for this study) revealed values that were marginally lower than the SMA, which may indicate a lower risk of damage when interpreting workload thresholds.

However, weak correlations imply that further data gathering and different analytical strategies may be required to completely comprehend the underlying dynamics of these interactions. To have more in-depth understanding, future studies should think about increasing the sample size, adding more variables, and possibly using mixed-methods techniques. Advanced statistical methods, like multivariable regression models, may also be able to identify patterns that more straightforward analysis might have missed. This thorough approach may improve knowledge of and use of tools like ACWR in sports analytics.

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