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A Brief Study on Professional soccer players' training and match loads compared to their Metabolic and Running speed parameters, stratified by position

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ABSTRACT

The purpose of this research was to examine the correlation between metabolic and running speed measurements, as well as to compare the training and match load of professional soccer players based on their playing position. Using GPS trackers (GPEXE Pro 18.18 Hz) in both training and games (n = 36 training weeks and n = 41 matches), the performance of 30 professional male soccer players from a club and district level players of Maharashtra was assessed. The results showed that there were significant differences between positions on game day: central midfielders ran farther than central defenders, external defenders, and forwards, and at a slower pace; forwards executed more metabolic power incidents than central defenders, central midfielders, and wide midfielders, and at a slower pace; and central defenders ran the least at very high speeds. During training, many patterns manifested themselves. In addition, there was a significant relationship between accelerations and decelerations as measured by the equivalent-distance index. Major takeaways include: metabolic power events and the equivalent-distance index appear to be parameters that assist in identifying more clearly the features of the player, taking their playing position into account; traditional and metabolic approaches ought to be used together for monitoring load in professional soccer players; and the physical responses found in training do not correspond with match demands by position.

Keyword: Physical responsesTime motion analysisMetabolic powerGPS ,CompetitionPerformance

INTRODUCTION

Because of the strenuous physical demands of professional soccer, it is essential for coaches and trainers to keep an eye on their players' training loads (TLs) to make sure that their athletes are getting the most out of their workouts and minimising their risk of injury. A high number of matches played over the course of a season can increase the risk of injury for professional players [1,2]. In team sports like soccer, where players compete once or twice weekly and show large load variability between training days (TDs) and positions [3,4], the load timing is frequently created by weekly micro cycles based on match day (MD), which typically coincides on weekends [5,6]. Players prepare for competition, so it makes sense to tailor the TL's training to actual game conditions. In order to keep up with the position-specific demands and requirements of the competition, it is crucial to keep an eye on and programme TL. Players at the highest level of the sport are under increasing pressure, and they must train for every possible outcome of a match [7]. Most research examine time-motion variables for monitoring training and matches based on running speed or intensity thresholds, such as distance covered across various speed ranges, high-intensity events, or the amount of acceleration and deceleration events [8]. There are those who believe that the metabolic approach is a more accurate way to calculate the energy cost of locomotion activities like accelerations and decelerations or distances wrapped at different speeds per unit of time, despite the fact that the traditional running speed-based approach is accepted as valid for load monitoring. When many locomotion activities are examined together, the athlete's aerobic capacity can be accurately estimated by the use of these metabolic variables, which measure the energy supply [9]. The EDI, which measures how much ground a player would have covered at a constant speed if he or she had used all of the energy they expended during the game as fuel, is one metric that can capture the sporadic character of soccer [11]. Furthermore, Castagna et al. [10] discovered favourable associations between metabolic and running speed measurements, lending credence to the adequacy of this method for representing high-velocity exercise. Despite the importance of monitoring training and game loads for each position, there is currently a dearth of studies assessing the variables of the metabolic approach (e.g., average metabolic power, maximal power, or power events) and their correlation with running speed-based measures. It is the opinion of the authors that a more complete understanding of physical needs and thus better load programming throughout the microcycle may be achieved by taking into account factors from both techniques during load monitoring. We presume that there are varying physical requirements according to position and that TL should be designed to satisfy the competition demands [12], although there may be a good correlation between the two techniques. The authors hypothesise that inadequate TL programming results in a training load that is insufficient to meet the competitive needs per post. This study has two objectives, then: The goals of this study were (1) to examine the association between metabolic and running speed measurements in professional soccer players from a Spanish First Division team, and (2) to compare the metabolic and traditional running speed-based techniques in training and competition by playing position. These findings may shed light on the roles that place insufficient demands on TDs with respect to MD, as well as the particular metrics to account in order to keep tabs on the load.

MATERIALSANDMETHODS

Subjects

30 professional male soccer players from a district level Football team in Maharashtra participated in this study during the 2021-2022 season (22.8 0.8 years; 177.8 6.9 cm; 73.3 5.7 kg). Players were classified by playing position [9, 10, 18]: central defender (CD), external defender (ED), central midfielder (CM), wide midfielder (WM) and forward. Maximum oxygen consumption (VO2) for these positions ranged from 6.590.95 to 6.610.92 to 7.221.05 to 6.911.03 to 6.880.99 litres per minute, respectively. The analysis also did not include goalkeepers.

Instruments

Wearable GPS devices (GPEXE Pro 18.18 Hz, GPEXE, Udine, Italy) were used to collect all data. High-quality GPS devices are useful for tracking the movements of professional soccer players during games and practises [5, 9, 12]. Because of the potential for GPS activation issues and delays, the participants received their gadgets 15 minutes before the start of the game. Eight times one is the number of satellites used in both practise and competition.

Procedures

Data on training and match loads were collected throughout the season to reflect the competitive period. In order to reduce potential training record fluctuations, preseason and off-season data were not included. Training logs for two-game weeks, sessions focused solely on tactics, and those of players who did not finish the entire session were also left out of the study. Only players with at least 80 minutes of action were included in the match analysis. In the end, data from 33 weeks of practise and 38 games was evaluated. Four days before the match (MD-4), three days before the match (MD-3), two days before the match (MD-2), and one day before the match (MD-1) were used to categorise the data. Due to the lack of particular and representative material in training sessions prior to MD-4, which are typically directed towards recuperation [9, 19], these records were excluded from the study.

Variables

In this research, both metabolic and speed-based measures of running were evaluated. All of these factors have been provided by GPS units themselves. Here are some measures of how fast you can run: number of acceleration events (ACC), defined as the number of times the vehicle's speed increased by 2 metres per second or more in a time interval of 0.5 seconds or less; number of deceleration events (DEC), defined as the number of times the vehicle's speed decreased by 2 metres per second or more in a time interval of 0.5 seconds or less; distance travelled in its various forms, including the total distance, the distance travelled at speeds below 14 kilometres per hour (km/h), the distance travelled at speeds between 18 and 21 kilometres per hour (km/h), the distance travelled at speeds between 21 and 24 kilometres per hour (km/h), and the distance travelled at speeds above 24 kilometres per hour (km/h). Metric measurements were used for everything. The metabolic measurements, on the other hand, can be used to estimate the energy cost of accelerations and decelerations during soccer's intermittent activity, and they look like this: maximum power (Pmax, in Wkg-1), peak energy reached during the activity; number of high-intensity events (power events); average metabolic power from actions developed at high intensity 20 Wkg-1 (MPev, on Wkg-1); and equivalent distance index (EDI, as a percentage), the percentage of distance that the player would have run at a constant pace using the total energy expended during the activity. The formula for calculating this measure is as follows: ED (m) = energy expenditure (J kg1) / energy cost (3.6 J kg1 m2) [20].

Statistical Analysis

We used IBM SPSS Statistics 25.0 for Windows and Microsoft Excel 2016. Almost none of the data showed a normal distribution, as shown by the Kolmogorov-Smirnov test. On MD-4, only MP and power events followed a normal distribution; on MD-3, ACC, MSRD, and MPev; on MD-2, DEC, total distance, MSRD, EDI, and Pmax; and on MD-1, only MP. To investigate the variations in roles between training sessions, we ran Kruskal-Wallis tests (for non-normal data) and analysis of variance (for normal data). The Mann-Whitney U-test and the Bonferroni test were used for the post hoc analysis. When the parametric data showed non-homogeneous variances, Dunnett's T3 test was used (MSRD and MPev on MD-3). The significance of the change was assessed by calculating the effect size. Parametric and nonparametric variables alike have been demonstrated to benefit from using the eta-squared (2) for effect size calculations [13]. Effect size cutoff values ranged from 0.10 for very modest impacts to 0.40 for extremely significant effects [14]. The coefficient of variation (CV) was computed for each position across training days to ascertain the within-subject variability of dependent variables. The motion activities and metabolic responses were then subjected to a correlation analysis (Spearman's coefficient test). The strength of the association was understood to be: Below 0.1 is inconsequential; between 0.1 and 0.3 is modest; between 0.5 and 0.7 is sizable; between 0.7 and 0.9 is enormous; and between 0.9 and 1.0 is nearly ideal [15]. The significance level was determined to be p <=.05.

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TABLE 1. Comparative data (mean ± SD) and eta-squared (h^2) results of locomotion activities based on running speed betweenmicrocycledaysbyplayingposition.Samplesize:CD(N=89),ED(N=61),CM(N=71),WM(N=76)andFO(N=36).

Var.	Position	MD-4	MD-3	MD-2	MD-1	MD	p	h^2
ACC	CD	49±17.8	42.4±13.8	38±14.9	32±8.2^{e}	68.5±13.0^{c,e}	.08	.01
	ED	45.9±17.2	41.9±12.5	36.1±13.2	31.2±8.5^{e}	63.4±11.3^{c,e}	.00	.04
	CM	42.7±19.7	39.5±14^{d,e}	33.7±16.6^{e}	30.6±11.1^{e}	81.9±21.2^{a,b}	.03	.03
	WM	47.6±18.6	45.1±17.1^{c}	40.1±16.2	32.2±10.8^{e}	68.7±16^{c}	.00	.07
	FO	51.3±21.9	48.8±14.9^{c}	43.1±14.1^{c}	41.1±10.9^{+}	82.2±16.5^{a,b}	.00	.16
DEC	CD	44.1±18.6	39.6±13.2^{e}	34.3±14.2	29.2±10.5^{e}	70.6±15.7^{c,d,e}	.20	.01
	ED	44.3±18.5	41.8±12.3^{e}	36.3±14.8	29.6±8.9^{e}	75.3±11^{c,e}	.00	.03
	CM	42.8±19.1	39.7±15.4^{e}	36±17.2	30.4±11.9^{e}	104.4±25.9^{a,b,d}	.12	.03
	WM	42.7±16.7	41.9±15.3^{e}	36.6±14.7	28.8±9.8^{e}	81.8±14.5^{a,c}	.00	.05
	FO	51.2±23.8	49.1±16.1^{+}	43.9±13.7	37.4±10.2^{+}	95.8 ±22^{a,b}	.00	.34
Total Distance(	CD	5136.4±1086.7	4428.9±1125.8	3763.3±899.8	3351.2±736.7	8939.4±1259.2^{c,d}	.20	.01
	ED	5017.8±1142.1	4548.5±983.8	3801.2±945.6	3315.9±733.3	9050.7±642.1^{c,d}	.25	.00
	CM	5306.5±1163.3	4687.7±1375.2	3973.4±948	3611.7±798.7	10760±775.2^{a,b,e}	.67	.01
	WM	5112.7±1302.5	4628.2±1091	3970.3±911	3412.5±749.9	9857.6±1688.2^{a,b}	.12	.01
	FO	5060.7±1257.4	4467.7±1217.9	3844.9±826.3	3474.2±751.7	9182.5±1953.5^{c}	.00	.39
LSRD	CD	4141.6±1061.6	3726.8±920.9	3266.2±715.7	2919.9±623.7	7445.7±1039.9^{c}	.21	.01
	ED	3968.7±1078.5	3702.6±798	3202.9±746.8	2832.5±560.8	7322.1±469.7^{c}	.15	.01
	CM	4195.5±1248.6	3865.5±1073.2	3412.4±717.5	3108.2±634.4	8227.7±460.1^{+}	.73	.01
	WM	4018.3±1142.3	3707.5±863.7	3317.4±688.6	2846.7±577.1	7619.2±1209.7^{c}	.05	.02
	FO	3872.3±1173.9	3596.4±948.8	3183.2±637	2866.1±559.1	6940.8±1376.8^{c}	.00	.28
MSRD	CD	705.8±785.5	417.9±172^{c,d}	335±158.9	287±101.4^{c,e}	896.7±187.9^{c,d}	.02	.02
	ED	681.4±857.8^{c}	442.6±149.4^{c}	350.4±170.3	278.8±108.8^{c,e}	913.7±177^{c,d}	.00	.05
	CM	789.1±787.6^{b}	535.7±251.9^{a,b}	403.8±180.7	357.4±147.8^{a,b}	1572.9±304^{a,b,e}	.09	.04
	WM	700.9±685	494.5±160.8^{a}	394.9±157.5	319.9±120.8	1270.4±373.8^{a,b,c}	.00	.04
	FO	763.2±776.2	484.7±179.1	412.2±137.6	345±116.5^{a,b}	1029±237.1^{c}	.00	.46
HSRD	CD	182.6±86.7^{e}	166±120.3^{b,d,e}	104.5±69.8^{d}	90.3±45.1^{d,e}	326.4 ±88.2^{c,d,e}	.01	.02
	ED	205.4±99.7	201.8±97.2^{a}	138.0±78.8	106.7±53.3^{e}	381.8±95.6^{c,d}	.00	.05
	CM	230.7±235.2	186.6±130.3^{d}	111.5±75.8	102.4±56.3^{d,e}	543.2±126.8^{a,b}	.01	.05
	WM	231.9±115.3	220.9±100^{a,c}	144.8±76.5^{a}	134.6±78.3^{a,c}	508.9±159.5^{a,b}	.00	.09
	FO	271.5±197.8^{a}	213.5±103.6^{a}	149.3±76.3	146.7±64.9^{a,b,c}	498.5±144.2^{a}	.00	.39
VHSRD	CD	73.6±58.2^{b,d}	81.5±80.5^{b,d,e}	41.6±38.2^{b,d,e}	39.9±34.1^{b,d,e}	161.5±61.8^{x}	.00	.06
	ED	104.3±66.4^{a,c}	121.8±85.2^{a,c}	69.3±51.7^{a,c}	60.5±42.4^{a,c}	234.6±84.1^{a}	.00	.09
	CM	67.9±60.5^{b,d}	77.7±75.8^{b,d,e}	36.8±31.8^{b,d,e}	34.9±28^{b,d,e}	252.4±98.4^{a}	.00	.12
	WM	100.9±66.9^{a,c}	130.8±99.3^{a,c}	75.4±51.6^{a,c}	70.9±54.8^{a,c}	252.8±95.6^{a}	.00	.13
	FO	98.7±70.6	112.5±86.5^{a,c}	70.7±45.9^{c}	78.9±58.2^{a,c}	336.8±136.5^{a}	.00	.26

SPD(m)	CD	32.9±47.2^{b,d}	36.9±53.8^{b,d,e}	16.2±22.6^{b,d,e}	14.2±20.2^{b,d,e}	108.9±62.9^{b,d,e}	.00	.08
	ED	58.1±55.7^{a,c}	79.8±66.6^{a,c}	40.7±36.9^{a,c}	37.5±44.2^{a,c}	198.5±87.1^{a,c}	.00	.16
	CM	23.4±32.3^{b,d}	22.3±29.3^{b,d,e}	9.1±12.8^{b,d,e}	8.8±12.7^{b,d,e}	163.7±128.3^{b,d,e}	.00	.17
	WM	60.9±66.9^{a,c}	74.7±75^{a,c}	37.8±35.4^{a,c}	40.4±64.1^{a,c}	206.3±147.7^{a,c}	.00	.11
	FO	55.1±65.1	60.8±67.3^{a,c}	29.6±24.6^{a,c}	37.6±43.7^{a,c}	377.4±215^{a,c}	.00	.21

Note:Var.,variable;ACC,accelerationevents;DEC,decelerationevents;LSRD(<14km·h^{-1});MSRD,(14to18km·h^{-1});HSRD(18to21km·h^{-1});VHSRD(21to24km·h^{-1});SPD(>24km·h^{-1});+,significantlyhigherthanallothervariables;x,significantlylowerthanallothervariables;a,staticallysignificantdifferencewithCD;b,staticallysignificantdifferencewithED;c,staticallysignificantdifferencewithCM;d,staticallysignificantdifferencewithWM;e,staticallysignificantdifferencewithFO.

RESULT AND DISCUSSION

The Conventional Method, which Focuses on Running Speed

Table 1 compares the standard metrics based on running speed from pre-microcycle days to post-microcycle days, broken down by position. Both in-game and off-season performance varied significantly. Across the board, training metrics were lower than MD metrics. Compared to CDs and EDs, FOs in MD showed superior ACC and DEC performance. Greater total distance, MSRD, and HSRD were observed for CMs compared to CDs, EDs, and FOs (10760.0 775.2 vs 8939.4 1259.2, 9050.7 642.1, and 9182.5 1953.5 m, respectively; 2 =.39). ACCs were higher for CMs compared to CDs and EDs. The shortest SPD was covered by CDs (108.9 62.9 m) and CMs (163.7 128.3 m) (2 =.21), and the shortest VHSRD was recorded by CDs (161.5 61.8 m) (2 =.26). Compared to CDs, EDs, and CMs, FOs in MD-1 had higher ACCs (41.1 10.9 events), DECs (37.4 10.2 events), and HSRD (134.6 78.3 m; 2 =.09). Again, CDs and CMs had the shortest SPD (40.4 64.1 m compared to 14.2 20.2 and 8.8 12.7 m, respectively; 2 =.11). On MD-3, FOs also conducted the highest volume of DEC (49.1 16.1 events). Different MD by position patterns were seen, however, when the CV was taken into account (Figure 1a). The CVs increased with increasing speed.The purpose of this research was to examine and evaluate the training and match load of professional soccer players by playing position using both a metabolic and a running speed-based approach. One of the most physically demanding positions in competition was centre midfielder (high values of total distance, total high-intensity distance, ACCs, and DECs). This was one of the primary conclusions. When compared to other positions in training, CM also demonstrated reduced physical reactions, which suggests that 3) TL does not correspond to the match load [16]. Finally, because of the high-intensity and intermittent nature of soccer, 5) MPev and EDI may be considered relevant variables to represent the physical performance in soccer; and 6) practitioners should consider both the metabolic and traditional ap- proaches together for load monitoring and programming.

Across the board, MD elicited the strongest bodily responses throughout the microcycle [17]. Since it is commonly recognised that 'players train to compete,' and the primary physical purpose of training is to survive the pressures of competition [18], these findings make sense. Consistent with the findings of other writers [19], we found that CMs averaged the most overall distance, high-intensity distance, DEC events, ACCs, and FOs each match. One possible explanation for these inflated expectations is the growing role of CMs in games' offensive and defensive phases [20]. Schuth, Carr, Blanes, et al. [21] came to the conclusion that central midfielders may have to resort to more strenuous ACCs and DECs due to the lack of space in the pitch's middle. Therefore, it may imply that the distinct role of CMs in the game according to the playing style [22] is the cause of the higher number of ACC and DEC events. For example, if the team loses possession of the ball, the central midfielders typically have to press directly on the opponent with the ball or support the pressing colleague to temporise and avoid a counterattack [23]. When compared to other occupations, CMs had the best results on MD-related tests. In contrast, different trends emerged throughout training, with CMs displaying the fewest ACCs and DECs on a TD average. Also, when comparing MD and TD, FOs had the highest SPD and VHSRD. These findings imply that TL does not correspond to match demands, which makes sense when you consider the differences in distance covered at high intensity between different positions in a game and in training. Coaches may have used central midfielders (CMs) 'to support' the specific tasks of other positions, such as the final sprint of wing players for cross- ing the ball into the box or when FOs try to dribble past defenders for penetration into the opponent penalty area, so that CMs showed very high variability between training and match loads [24]. For instance, wing players (EDs and WMs) and FOs are typically tasked with 'crosses and shots to goal,' while CMs typically support the exercise by passing or acting in the second phase.

Therefore, it is suggested that the activities, or even specific motions or actions within the tasks, be designed to mimic the physical requirements of the position in addition to the technical-tactical necessities.

Physically, CDs and EDs were very similar to one another in many different ways (for example, in ACCs, DECs, total distance, MP or power events, and many more). It's possible that the team's proposed playing style [25]—which positions the 'closed' defensive line in the central area, limiting EDs' attacking opportunities and leaving a greater responsibility for WMs to carry out the offensive actions on wings while also developing their defensive duties—explains the generally similar performance found in defensive positions. Even though EDs are more likely to run towards their own goal to defend it, their elevated values in the highest intensity measures (SPD, VHSRD, Pmax, and MPev) suggest that they may also be involved in offensive actions on wings, such as counterattacks. In fact, many writers have lumped all wing players (i.e., EDs and WMs) into the same category as 'wings' because of the similar physical performance they generate . Although both WMs and EDs may have similar physical demands, the sort of effort may be different (i.e., attacking vs. defending), making it confusing to discuss them together. As a result, it demonstrates the significance of tailoring a player's TL to their position and playing style [25].

CONCLUSION

Expertise in controlling workload is crucial for practitioners, especially at the highest levels of soccer. Programming the load among TDs in relation to match load by position is an excellent approach for load monitoring because players practise to obtain strong performance in competition (i.e., on MD). When determining the physical demands of soccer players, it is important to take into account both metabolic and conventional running speed-based techniques to monitoring and training. When considering the various roles that players fill, EDI and MPev stand out as promising indicators for making distinctions between them. Finally, practitioners need to put more effort into creating training assignments that result in position-specific TL.

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