Unlocking Performance Insights: IMU-derived Power Monitoring in wheelchair basketball over multiple games

By

Victor Thomas Goené

In partial fulfilment of the requirements for the degree of
Master of Science in Biomedical Engineering
Track: Neuromusculoskeletal Biomechanics
At the Delft University of Technology
Faculty of Mechanical Engineering

To be defended publicly on Monday August 26, 2024 at 13:45

Student number:	5400074
Date:	August 2024
Supervisors:	Prof. dr. H. E. J. Veeger (chair)
	PhD. M. P. van Dijk (supervisor)
	Prof. dr. ir. J. Harlaar (Committee member)

Abstract

Wheelchair basketball has become increasingly popular, leading to a rise in professionalism. While performance measures exist, they lack objective metrics directly related to an athlete's individual load that can be measured during games. An objective measure related to the athlete's load can provide information about fatigue and the total load of training or matches. A recent study presented a theoretical framework for calculating power during games. This study aims to examine the utilization of power metrics derived from Inertial Measurement Units (IMUs) in wheelchair basketball using the theoretical framework, focusing on power produced during straight-line sprinting in matches. This will be done by answering the main question of this paper: How can individualized power metrics for performance monitoring be derived during wheelchair basketball match play using IMUs? Eight female participants from the Dutch national wheelchair basketball team were assessed in twelve international practice games using IMUs on their wheelchairs. Power profiles were created based on sprint power, offering insight into sprint powers and their distribution. Work done, determined from power output and push duration, provided insights into athlete fatigue during games. Power profiles can be used to monitor long-term performance, either between games or between seasons. Regression analysis showed a significant positive effect of classification scores on single push power output, with an R-squared value of 0.75. This study proposes areas for future research, including integrating trunk motion analysis and exploring the effects of different player positions on power profiles. By enhancing the understanding of player performance, these findings contribute to the professionalization of wheelchair basketball, aiming to optimize performance and reduce injury risks.

Index Terms

Mechanical power, Power profile, Work, Wheelchair sports, Inertial measurement unit, Wheelchair propulsion, Rolling resistance force

I. Introduction

A. Beginning of performance measuring in wheelchair basketball

After the Second World War, veterans started playing wheelchair basketball. It gained popularity and became one of the sports in the first-ever Paralympic games (IWBF, n.d.). By gaining popularity, the competition increased and consequently, the professionalism increased. This resulted in athletes and coaches searching for ways to enhance performance. One of the first studies into wheelchair basketball performance during games was that of Byrnes et al. (1994). This study determined the athlete's contribution to a game as a performance measure. Performance measures are quantitative indicators utilized to compare athletes across different games and among athletes. After this initial research, subsequent studies further explored wheelchair basketball performance, revealing that mobility performance, which encompasses wheelchair handling skills (Veeger et al., 2017), could serve as a valuable performance measure (Rhodes et al., 2015, Sarro et al., 2010, Usma-Alvarez et al., 2010). With the use of Inertial Measurement Units (IMUs), van der Slikke et al. (2016) could create six key features to describe wheelchair mobility performance in match play accurately. These features are average speed, average max speed, average acceleration, average rotational speed in a curve, average max rotational speed in turn, and average rotational acceleration. Enhancing these skills not only contributes to athletes' overall performance but also aids in their ability to navigate the court effectively.

B. Introduction of power

While previous studies in wheelchair basketball performance provided quantifiable metrics for mobility performance, they lacked objective measures directly related to an athlete's individual load that could be measured during games. An objective measure related to the athlete's load can give information about, for instance, fatigue or the total load of a training or match. The information provided by objective measures can aid coaches in athlete monitoring and reducing injury risks (van Dijk et al., 2024, Halson, 2014, Soligard et al., 2016, Mujika, 2016). Heart rate is not an option given the delayed response, it would result in an underestimation of sprint effort. Furthermore, heart rate responses differ in Paralympic athletes, compared to able-bodied athletes (Paulson et al., 2015). Power is one of the most used objective metrics in other sports that is related to load and can be measured during games (Pelland-Leblanc et al., 2013, Barker et al., 2011, Waldron et al., 2015, Pinot and Grappe, 2011, Sanders et al., 2017a and Sanders et al., 2017b). This paper defines power as the mechanical power exchanged between the athlete and the environment (van Dijk et al., 2024b & Van der Kruk et al., 2018).

C. Theory behind calculating power

Despite its potential utility in wheelchair basketball, measuring power directly has been challenging. In a study by Miyazaki et al. (2020), a power-measuring device for wheelchair basketball was created. Like cycling, where a force sensor sits in the crank arm, they added force sensors to the push rim. However, this device was expensive and heavy, so measuring power directly is currently not viable (Chenier et al., 2021). Fortunately, a more feasible approach involves leveraging IMUs to calculate´ power, as demonstrated in other sports like cross-country skiing (Gløersen et al., 2018, Uddin et al., 2021, de Vette et al., 2022). Van Dijk et al. (2024b) presented a theoretical framework for monitoring mechanical power in wheelchair sports. This framework uses the power balance where the combination of the athlete and the wheelchair is considered as a rigid body. The power balance can be seen in Equation 1. The forces displayed in the equation are; the rolling resistance of the center of mass (COM) ($F_{roll,COM}$), the air resistance of the COM $F_{air,COM}$, and the gravitational resistance of the COM $F_{g,COM}$.

By multiplying the resistance forces with the velocity of the COM v_{COM} the power loss due to those resistance forces can be calculated. $\frac{1}{dt}(0.5 * m_{aw} * v_{COM}^2$ represents the power of the kinetic energy. m_{aw} represents the mass of the athlete and wheelchair (aw) combined. In this paper, gravitational resistance does not apply, since the athletes were measured in an indoor hall with horizontal flooring. Wheelchair basketball is an indoor court sport, therefore the air resistance can be considered negligibly small (Barbosa et al., 2014, van Dijk et al., 2024b). Van Dijk et al. (2024b) mention two different models to calculate power, one requires measurement of the v_{COM} and the other of v_{wc}. Many applications in cyclical sports use average power output per push (Holt et al., 2021, Leo et al., 2022), a method that may be transferable to wheelchair basketball. Over multiple propulsion cycles the average velocity of the COM $\overline{v_{COM}}$ equals the average velocity of the wheelchair $\overline{v_{wc}}$. With IMUs, it's possible to measure the velocity of the wheelchair accurately.

$$Power_{aw} = -F_{roll,COM} * v_{COM} - F_{air,COM} * v_{COM} - F_{g,COM} * v_{COM} + \frac{1}{dt}(0.5 * m_{aw} * v_{COM}^2) \quad (1)$$

D. Specific approach for this paper

The sport of wheelchair basketball is a very high-intensity sport. In other words, the athletes have to produce numerous sprints with little rest (Coutts, 1992, Croft et al., 2010, Molik et al., 2010). Since the knowledge about the rolling resistance during turning is limited it's currently too complicated to determine cornering power (van Dijk et al., 2024). Therefore, this study will focus on straight-line sprint power.

E. Power metrics

A review by Van der Slikke et al. (2022) showed that current monitoring tools lack individualization for performance monitoring. Furthermore, monitoring load has not been possible during competition.

In cycling, different power metrics are used (Sørensen et al., 2019 & Allen et al., 2019). Most of these metrics are based on power per given time. In wheelchair basketball, power over time will not be useful, since there is no continuous effort. So, this raises the question of which power metrics can be rewritten for wheelchair basketball. A metric that can be rewritten into power per push is a power profile, also known as the ”signature of the athlete” (Pinot and Grappe, 2011). An example of a power profile can be seen in Figure 1. But instead of power for 5 seconds or 5 minutes, it will be power for one or two pushes, etc. Power profiles are used for long- and short-term monitoring. Multiple power profiles can give mean and max values for the athlete, so single-game performance can be compared to the athlete's ability.

Power is also used to determine the intensity of a training session or race. In cycling training stress score (TSS) is used to give a value for the session's intensity and provide information about the required recovery (Sanders et al., 2017b & Sanders et al., 2017a). However, calculating TSS requires continuous effort and is therefore not possible to implement in wheelchair basketball. Fortunately, according to Erp et al. (2019), the amount of work done is a good predictor for TSS, and with IMU data, calculating the work done during a single push will be possible. Therefore, information about the work done during a game can provide insights into fatigue. If an athlete's work done per quarter or minute at the end of the game is lower than at the beginning, it could indicate that fatigue is becoming a factor.

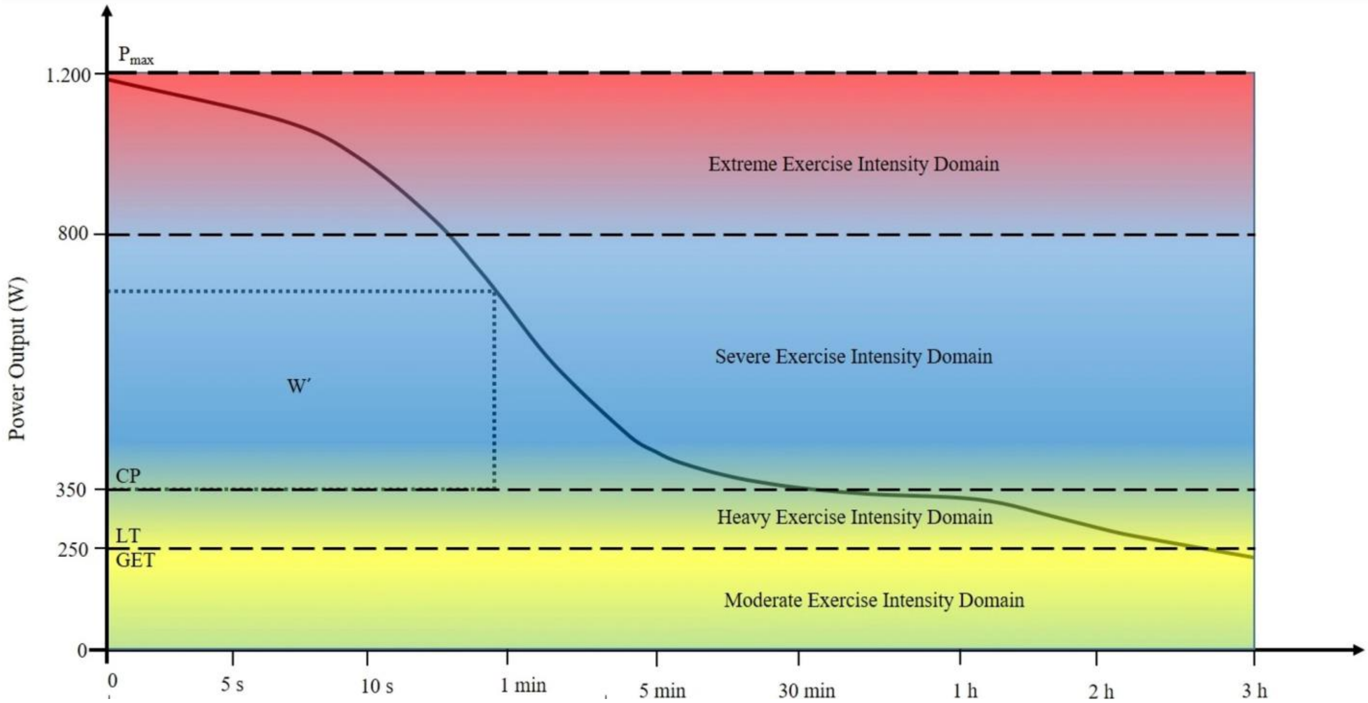


Fig. 1: Visual representation of a power profile. Adapted from Leo et al. (2022). Where Pmax is 1s peak power, W' is work above critical power, CP is critical power, LT is lactate threshold, GET is gas exchange threshold

F. Research gap and question

Despite advancements in performance monitoring, individualized power metrics tailored to the unique demands of wheelchair basketball are lacking. This study aims to fill this gap by deriving such metrics using IMUs. This leads to the following research question: What individualized power metrics for performance monitoring can be derived in wheelchair basketball match play using IMUs? This question will be answered by creating power profiles for long-term monitoring of individual athletes, showing the individualization. Also, the work done per minute and quarter will provide information about the intensity and possibly predict fatigue by lower values than in previous quarters.

II. Method

A. Experimental setup

This study was approved by the Ethics Committee of the Technical University of Delft. All participants signed an informed consent.

Eight female participants from the Dutch national wheelchair basketball team were measured in twelve international practice games in Papendal (Netherlands) between June 2021 and November 2022. The measurements were performed starting at the warm-up until the end of the game. During the first match the participants were aged 28.5 (± 7.4) with a mean classification of 2.9 (± 1.2), the distribution of the classifications and the number of games played can be seen in Table I. The classification of the athlete depends on the level of their disability, with a score of 1.0 indicating the most significant impairment and 4.5 indicating the least considerable impairment. During the warming-up of one of the games, every athlete performed three coast-down tests. A coast-down test is a test in which the athlete accelerates to get some speed and then sits completely still. This determines the speed loss over time, which is only related to the resistance forces since all non-resistance forces are zero. Detailed equations can be seen in Equation 2, a minus sign is introduced since deceleration is considered. During the coast-down test, the athletes were instructed to push three times and to sit upright with their hands on their lap after the third push. It is assumed that no changes were made to the equipment regarding wheel angle or tire pressure additionally, since all games were played in the same hall, the assumption was made that the rolling resistance coefficient calculated from one coast-down test can be applied to all games.

$$\{F = m * -a --> F = m * -\frac{dv}{dt}\}, \{F_{roll} = C_r * m * g\} -- > dv = -C_r * g * dt --> C_r = -\frac{\frac{dv}{dt}}{g} \quad (2)$$

Classifications	1	1.5	2	2.5	3	3.5	4	4.5
Number of athletes	1	1	1	0	1	1	2	1
Games played	11	4	9	0	8	6	4-10	11

TABLE I: Distribution of the classifications and number of games played

TABLE I: Distribution of the classifications and number of games played

B. Equipment

Two IMUs were used (MoveSense, Suunto Oy, Vantaa, Finland). One was placed on the frame's camber bar and one on the right wheel's axle, as seen in Figure 2. The IMUs only measured gyroscope data. Both IMUs had a sampling frequency of 100 Hz. The IMU data were collected via Wi-Fi using the wheelchair mobility performance monitor (WMPM) app (Van der Slikke et al., 2017), which automatically synchronizes the time between the sensors. The athletes and their wheelchairs were weighed independently using a scale. The camber angle and wheel circumference were measured before one of the games.

Fig. 2: Placement of the IMUs on the wheelchair

C. Analysis

The gyroscope data from the IMUs were imported and processed in Matlab (version 23.2.0.2515942, Mathworks, Natick, MA, United States of America). The data were filtered with a 2nd order low-pass recursive Butterworth filter with a cut-off frequency of 10 Hz (Van der Slikke et al., 2015). The gyroscope data were then used to calculate the frame speed (v_{frame}) and acceleration. Equation 3, Equation 4 and Equation 5 were used for calculating the frame speed. First, the angular velocity of the wheel (ω_{wheel}) is corrected since it is affected by frame rotations Van der Slikke et al. (2015). This can be corrected with the angular velocity of the frame (ω_{frame}). In the equations, ϕ_{camber} is the camber angle, and fs is the sample frequency. The acceleration is calculated by taking the derivative of the frame speed. These equations are based on the equations presented by van Dijk et al. (2021). The linear acceleration was then filtered with a sample frequency of 1.5 times the mean push frequency. The mean push frequency was considered the most prominent frequency, on the frequency spectrum, between 1.2 Hz and 3.5 Hz (Van der Slikke et al., 2016).

$$\omega_{wheel,corrected} = \omega_{wheel} - tan(\phi_{camber}) * \omega_{frame} * cos(\phi_{camber}) \quad (3)$$

$$v_{wheel} = \omega_{wheel,corrected} * wheelcircumfence \quad (4)$$

$$v_{frame} = v_{wheel} - (tan(\omega_{frame}/fs) * wheelbase/2) * fs \quad (5)$$

In this paper, gravitational resistance does not apply, since the athletes were measured in an indoor hall with horizontal flooring. Since the velocity was also not reaching speeds over 4.5 m/s, air resistance is considered negligibly small (Barbosa et al., 2014, van Dijk et al., 2024b). Rolling resistance is therefore the only resistance considered in this paper. The friction coefficient was calculated using a coast-down test to determine the rolling resistance. During the roll-out of the coast-down test, the only force acting on the wheelchair-athlete combination is rolling resistance. Therefore with a coast-down test, the friction coefficient was calculated. This was done by fitting a first-order polynomial after the last push of the test to determine the speed loss over time during the roll-out and using the slope coefficient to determine the rolling coefficient. The calculations can be seen in Equation 2. Where m is the mass of the wheelchair in and athlete in kg, g is the gravitational acceleration in m/s^2, $\frac{dv}{dt}$ is the change of velocity over time in m/s^2, and C_r is the roll resistance coefficient. Since deceleration is considered, a minus sign is used. A visual representation of the coasting tests can be seen in Figure 3, where the velocity of the wheelchair is plotted over time and the first-order polynomials are plotted from after the last push until the athlete makes a turn.

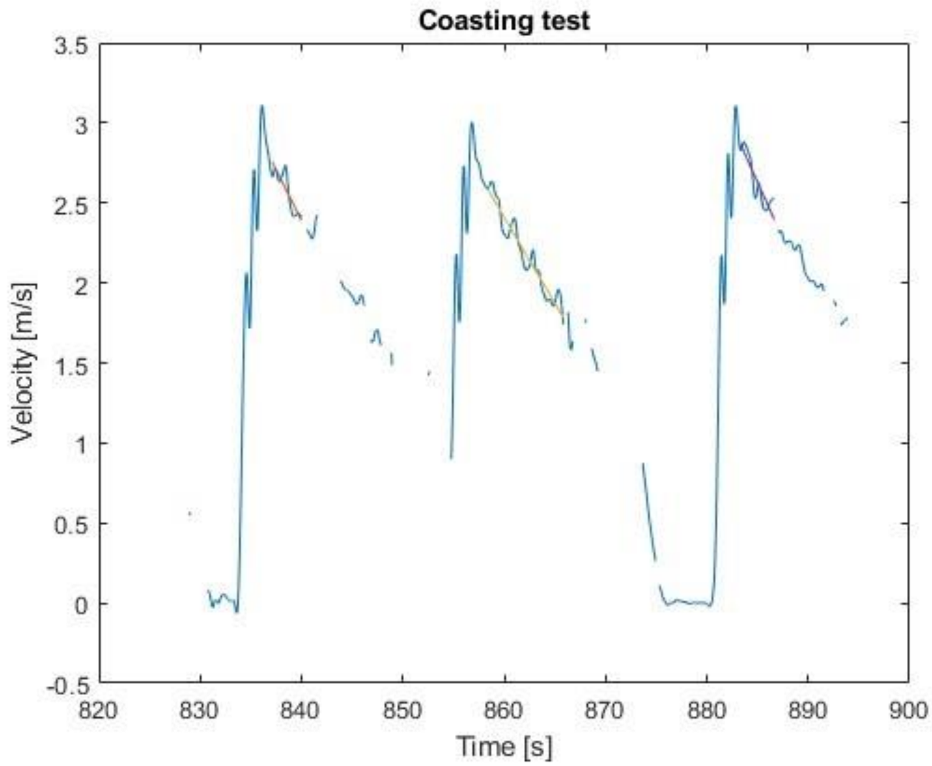


Fig. 3: Visual representation of the coasting tests with fitted line (only straight line data are plotted), the blue line represents the velocity of the wheelchair and athlete. The other colored lines are the first-order polynomials

Since this paper focuses on straight-line sprinting, direction changes had to be removed from the data. To determine straight lines and thus eliminate corners, the movement of the athletes was plotted. By choosing the maximum allowed angular velocity, it was possible to determine which value of angular velocity showed the best result. The best result was considered when only the straight-line movement of the athletes was plotted. An angular velocity threshold of 10 deg/s gave the required result. A push detection algorithm was made to detect the pushes during the game. An acceleration threshold of 0.5 m/s^2 was determined by examining the data. A push in this paper means a push cycle, the athlete starts and stops this cycle in the same position. The moment where the acceleration was zero before the threshold was reached is considered the start of the cycle. The end of the cycle is considered as the moment where the acceleration is zero after the velocity reaches a peak. By examining the data some cycles had a very short recovery phase of 0.05 s or less. Consequently, these pushes resulted in high power values that were considered abnormal. Janssen et al. (submitted) reported that the wheelchair acceleration continued 0.24-0.17 seconds after hand release, the recovery phase. Therefore, a minimal recovery phase of 0.15 seconds was added in this study. A visual representation can be seen in Figure 5 with the push cycles being the gray area under the plotted velocity. The acceleration is also plotted in red. If a push cycle was not starting and ending with acceleration zero, because only straight-line movement was used, this push cycle was not used in the calculations. This would have resulted in over- or underestimations of power.

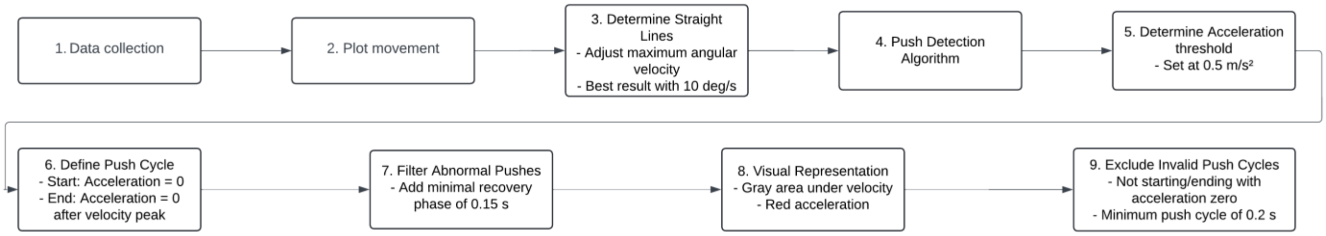


Fig. 4: Flow diagram of creating the MATLAB algorithm

Research by Janssen et al. (submitted) was used to determine a minimal push time. This study measured sprint characteristics from wheelchair tennis players. The results from this research showed a minimal push cycle of 0.25 seconds. As described earlier, a push cycle is a push with the recovery phase added. Upon closer inspection with a visual representation of the velocity, a minimal push cycle duration of 0.25 seconds excluded some full pushes. Therefore, a minimal push cycle of 0.20 seconds was used. To determine if a sprint was performed a minimal velocity needed to be reached. Based on the research of Janssen et al., submitted the minimal velocity was set at 3 m/s for a sprint with multiple pushes. The minimal velocity for a one-push sprint was set at 1.5 m/s. The power of the pushes was calculated using the power equation from the introduction Equation 1. In this case, the power of the kinetic energy was calculated with the following formula: $P_k = m * a_{wc} * v_{wc}$, and the power of the rolling resistance was calculated by multiplying the rolling resistance force and the velocity of the wheelchair: $P_f = F_{roll} * v_{wc}$ (van Dijk et al., 2021). After calculating the power per push and power per sprint, multiple performance metrics were calculated. Those are power profile and anaerobic load.

Two power profiles were created. Creating both power profiles involved calculating the mean of the highest three values per push number or consecutive pushes within each game. Subsequently, the mean power profile across all games was determined. The consecutive power profile is derived from the mean power output of consecutive pushes during a sprint. In contrast, the arranged power profile illustrates the power output specific to each push number during a sprint. Figure 5 shows a sprint of 8 pushes. For the consecutive power profile, this sprint will result in 36 values, 8 values for 1 push, 7 values of the mean of 2 consecutive pushes up to 1 value of the mean of 8 consecutive pushes. For the arranged power profile, this sprint will result in 8 values, one for each sprint number. Push 7 for example will give a value for the arranged power profile value push number 7. For easier interpretation, one value of the power profile will be displayed to compare all games played by a single athlete. For the consecutive power profile, this value will be the maximum power for one single push, later called single push power. For the arranged power profile, the value will be the mean of three consecutive pushes from the consecutive power profile.

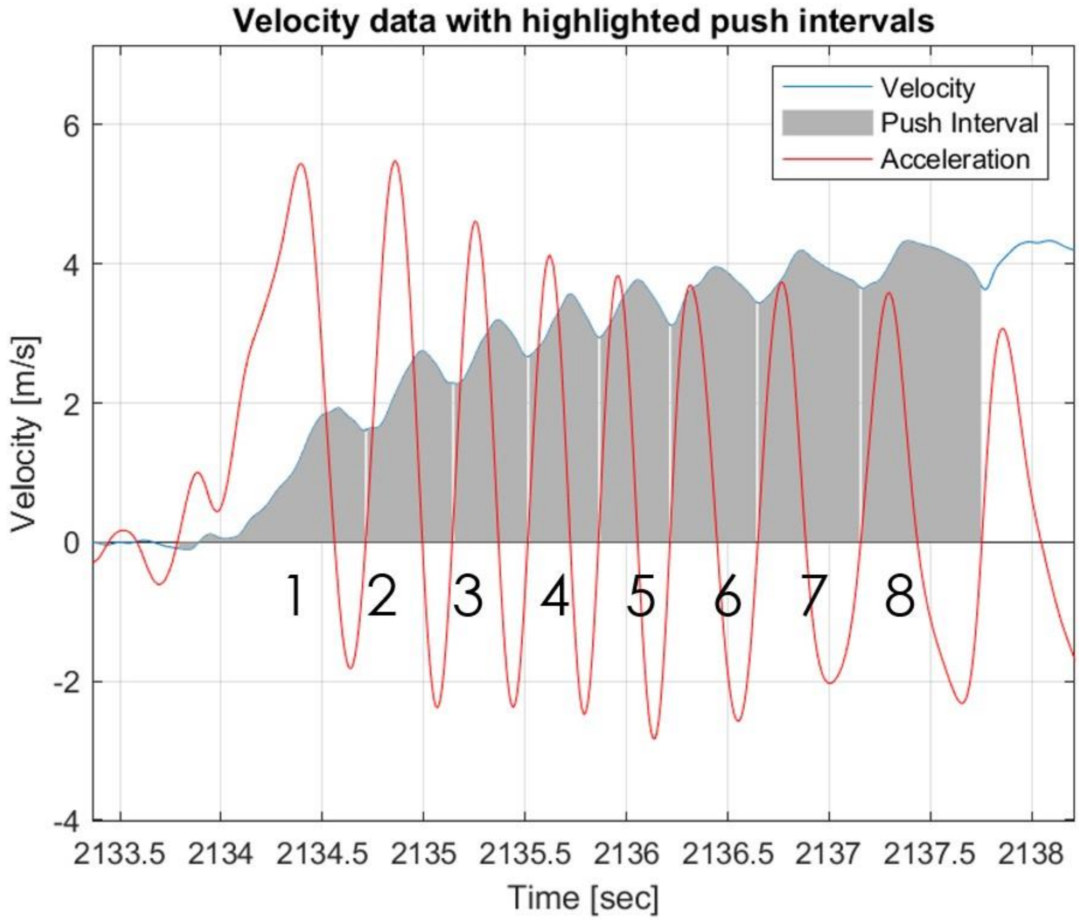


Fig. 5: Visual representation of a sprint (only straight-line data are plotted). This graph shows a sprint of eight pushes, starting from standing still, pushes are numbered. The total sprint time is around four seconds.

D. Statistics

Outcomes were tested with the Kolmogorov-Smirnov test for normal distribution. For displaying all power profiles, a correlation test was done between the individual values of the power profiles and the displayed value. For the consecutive power profile, this will be the single push power. For the arranged power profile, this will be the maximum value of the mean of three consecutive pushes. To determine the effect of classification on power output, a linear regression analysis was done between the classifications and the single-push power values of the power profiles.

III. Results

A. coast-down tests

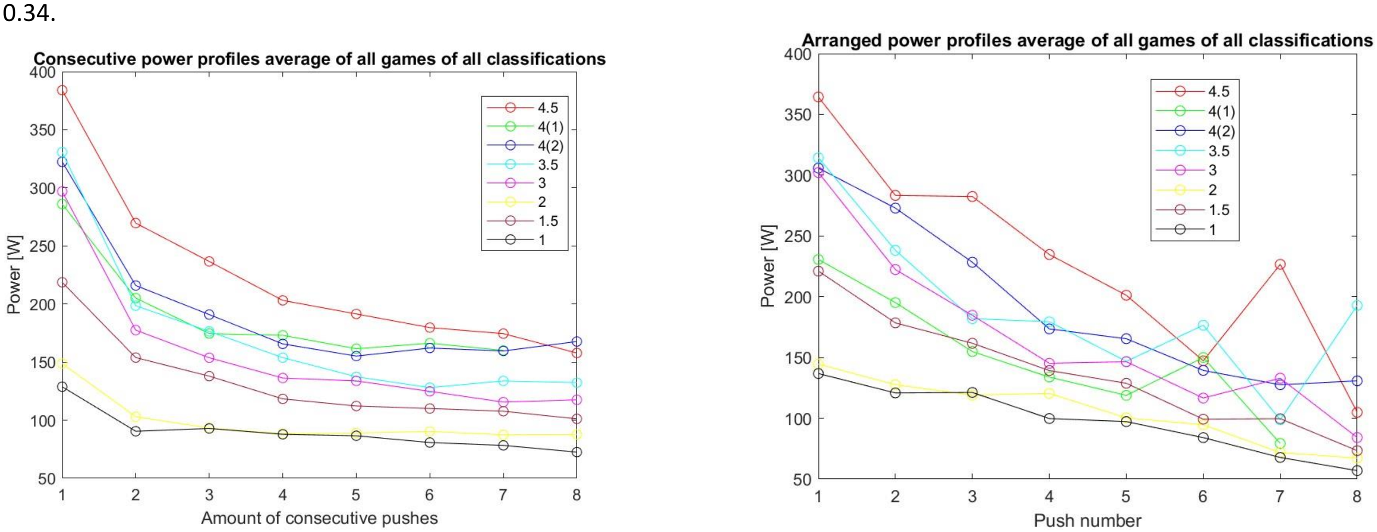
In total 63 games were analyzed, per athlete there were between four and eleven games. During one of the games, the coast-down tests resulted in a mean rolling coefficient (μ_r) of 0.125 (± 0.0055). This resulted in a mean rolling resistance of 8.99 N (± 3.68). A full overview of the rolling coefficient and rolling resistance for every athlete can be seen in Table II.

Classification	1	1.5	2	3	3.5	4(1)	4(2)	4.5
µ	0.015	0.014	0.008	0.007	0.012	0.010	0.010	0.024
F_{roll} (N)	10.0	9.8	5.6	4.7	8.6	8.9	7.6	16.8

TABLE II: Rolling coefficient and rolling resistance for every athlete, with μ being the rolling coefficient and F_{roll} being the rolling resistance force

B. Power profiles

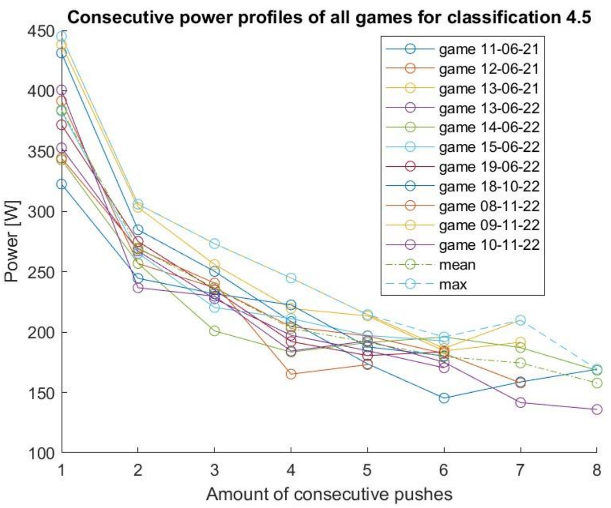
After calculating power, power profiles were created as described in the method section. This was done for every game of every athlete. Figure 6 shows the mean of all power profiles per athlete, Figure 7 shows all power profiles of one athlete.
This spread is similar to the spread for other athletes. The consecutive power profiles have little differences between them and follow the same trajectory. The arranged power profiles differ more however, there is a trend visible. Two visuals were created to monitor athlete performance over a longer period. The first visual showcases a full power profile from a certain period, providing a comprehensive overview of an athlete's performance throughout the entire period. This helps in understanding broader performance patterns and long-term progress or regression. The second visual represents a single value of the power profile per game, allowing for quick comparisons between individual games and identifying trends or anomalies in performance. These can be seen in Figure 8 and Figure 9 The value chosen for the consecutive power profile was the single push power since this value had a mean correlation of 0.46 with all other values. For the arranged power profile the value with the highest correlation with all values was the mean of three consecutive pushes from the consecutive power profile, with a correlation of 0.34.



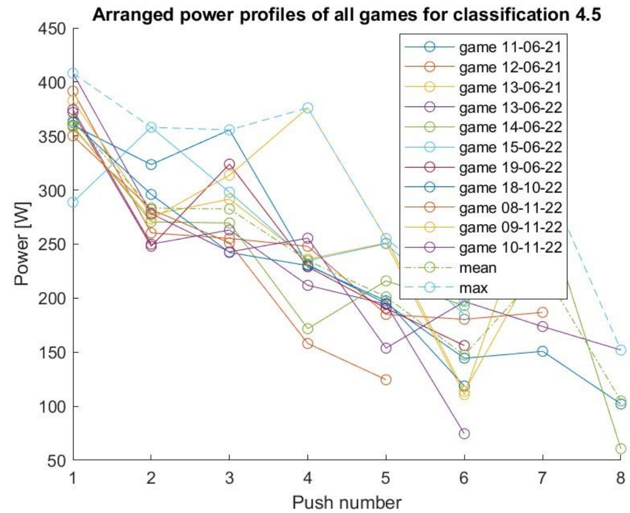
(a) Consecutive power profiles of all athletes. Calculated by taking the mean of all games for a single athlete.

(b) Arranged power profile of all athletes. Calculated by taking the mean of all games for a single athlete.

Fig. 6: Power profiles of all athletes. From these graphs, it is already visible that the higher-value classifications produce more power. Both power profiles show decreased power over consecutive pushes or push numbers. Each athlete has their own line, with the legend displaying their classification

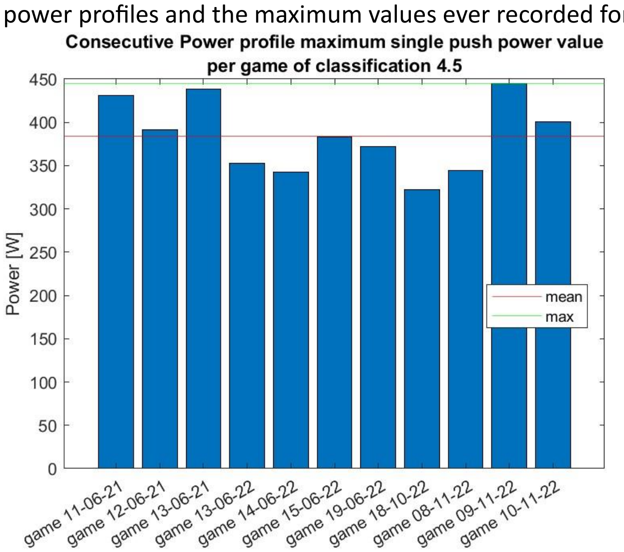


(a) Spread of consecutive power profiles of athlete with classification 4.5 including the mean of all consecutive power profiles and highest values ever recorded.

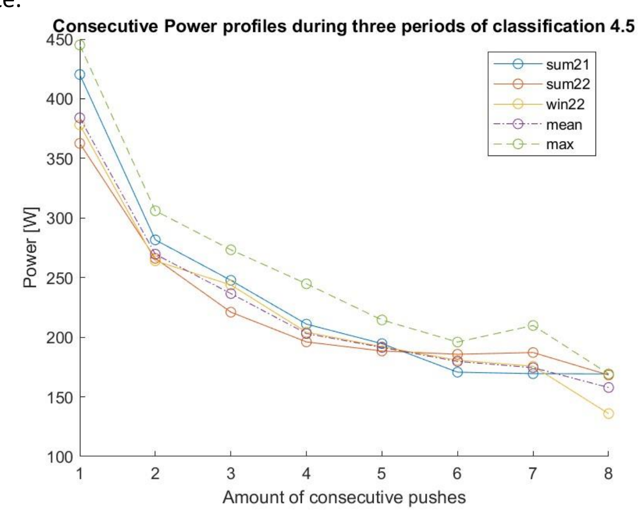


(b) Spread of arranged power profiles of athlete with classification 4.5 including mean of all consecutive power profiles and highest values ever recorded.

Fig. 7: All consecutive and arranged power profiles recorded of the athlete with classification 4.5. Also included are the mean power profiles and the maximum values ever recorded for this athlete.

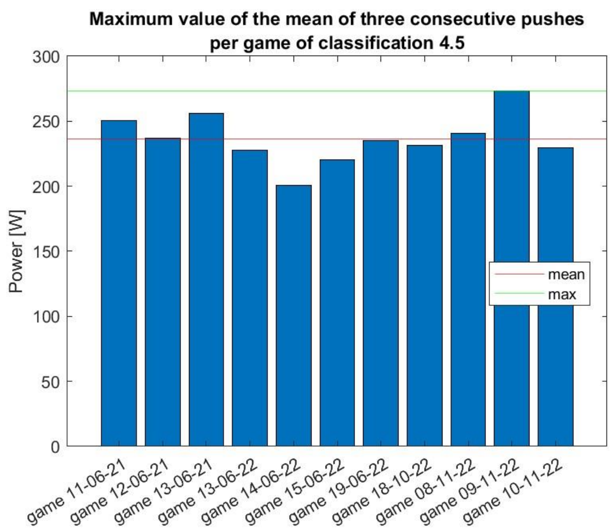


(a) Single push power value of every game of athlete with classification 4.5. The mean line represents the mean single push power of all games, the max value is the highest single push power recorded. Since all games are shown, this is equal to the highest bar.

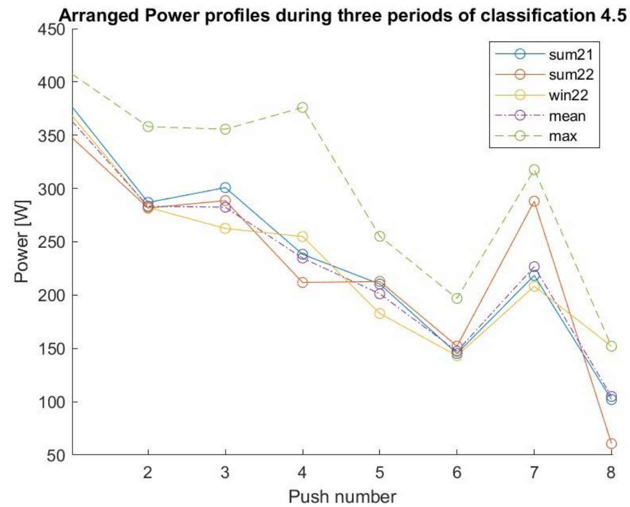


(b) Consecutive power profile per period of the athlete with classification 4.5, sum21 is the mean of all games of the summer season of 2021, sum22 is the mean of all games of the summer season of 2022 and win22 is the mean of all games of the winter season of 2022. The mean value is the mean of all consecutive power profiles and the max is the highest value the athlete ever recorded, which can be from different games.

Fig. 8: Consecutive power profile per period and single push power value per game. Also included are the mean and max values of the athlete. In this figure single-game performance can be compared to all games and the periods can show long-term progression or regression, combining games reduces the effects of single-game performance and gives a more nuanced image of the performance difference.



(a) Maximum values of three consecutive pushes of every game of athlete with classification 4.5 The mean line represents the mean power of three consecutive pushes of all games, the max value is the highest power over three consecutive pushes ever recorded for this athlete. Since all games are shown, this is equal to the highest bar.



(b) Arranged power profile per period of the athlete with classification 4.5, sum21 is the mean of all games of the summer season of 2021, sum22 is the mean of all games of the summer season of 2022 and win22 is the mean of all games of the winter season of 2022. The mean value is the mean of all arranged power profiles and the max is the highest value the athlete ever recorded, which can be from different games.

Fig. 9: Arranged power profile per period and maximum of the mean of three consecutive pushes per game. Also included are the mean and max values of the athlete. In this figure single-game performance can be compared to all games and the periods can show long-term progression or regression, combining games reduces the effects of single-game performance and gives a more nuanced image of the performance difference.

A regression analysis was performed to determine the effect of classification on single-push power output. Power output was the dependent variable and classification was the independent variable. For power output, the single push power value was used. The slope of the regression line is 60.39, indicating that for each unit increase in the classification score, the power output increases by approximately 60 watts. This relationship is statistically significant with a p-value of 0.006 ($p < 0.05$), suggesting that there is a significant positive effect of classification scores on power output. The R-squared value of the model is 0.75, indicating that the classification scores can explain 75% of the power output variability. This shows a moderate/strong relationship between the variables. Figure 10 shows the scatter plot of power output against classification scores along with the fitted regression line, highlighting the positive relationship between the two variables. Table III shows the estimated coefficients of the linear regression model.

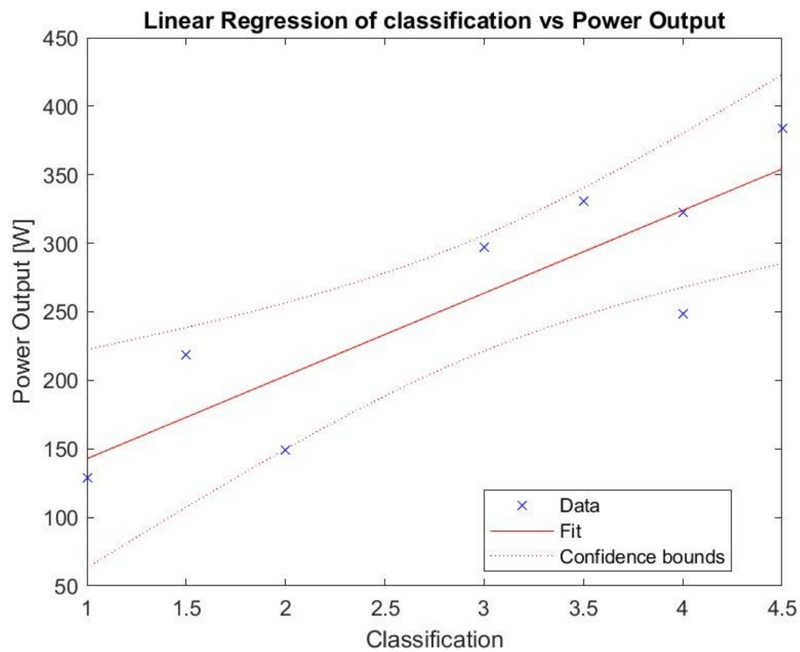


Fig. 10: Linear regression analysis

	Estimate	SE	tStat	pValue
(Intercept)	82.437	45.29	1.8202	0.11859
X1	60.394	14.255	4.2366	0.0054604

TABLE III: Estimated coefficients of the linear regression model

C. Work done

The amount of work done was calculated by multiplying the mean power per push with its respective push duration. Two versions were created, firstly a work done per minute and secondly, a work done per quarter. This was done for every athlete for every game. These graphs were combined and can be seen in Figure 11.

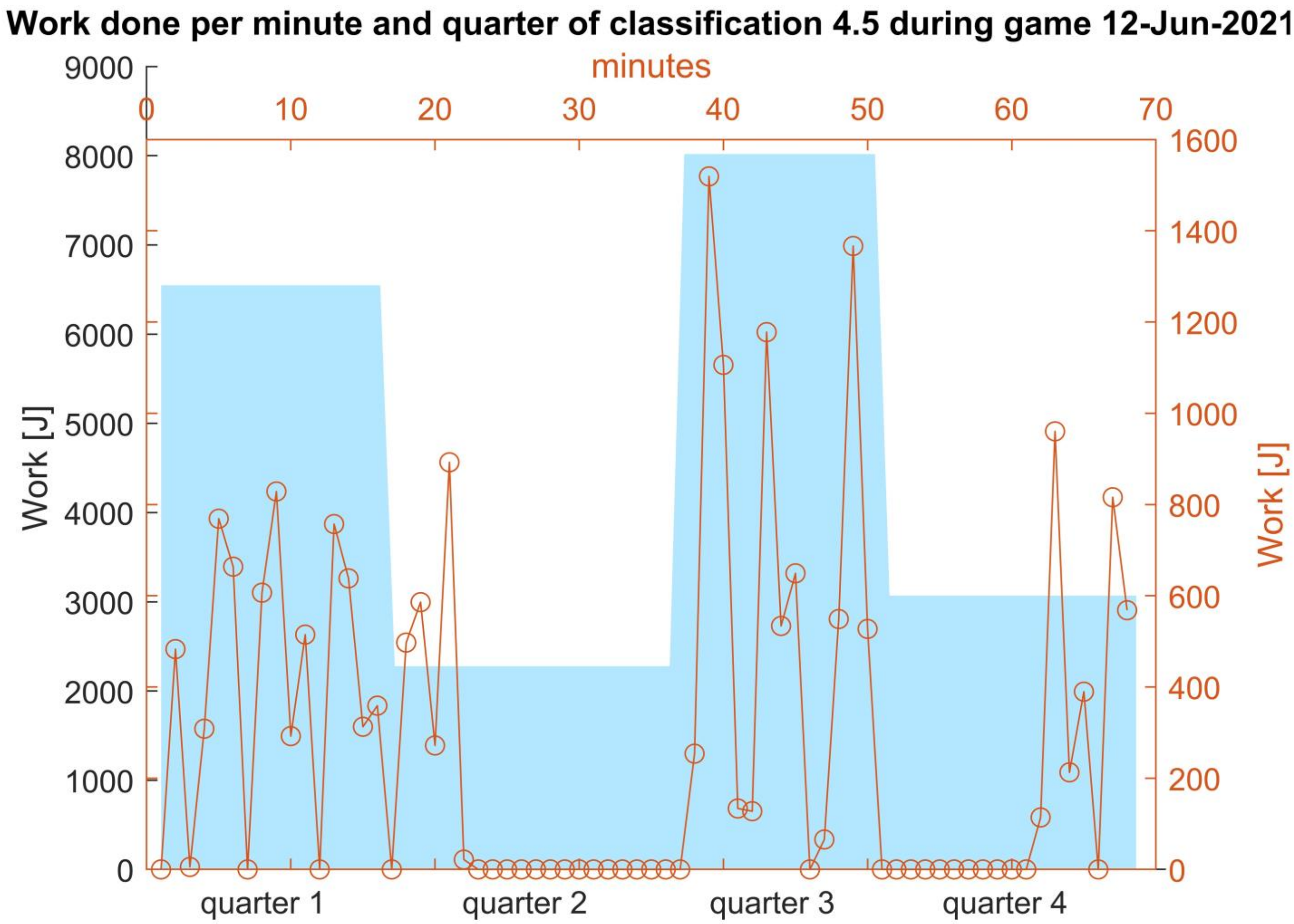


Fig. 11: Work done during a single game, per quarter and minute. The blue area is the total amount of work done per quarter and the connected orange dots are the amount of work done in that minute. More work was done in quarters one and three compared to quarters two and four. However, in quarters two and four she played for fewer minutes. The minutes played in quarter three show more work done per minute, suggesting this quarter to be the hardest during the game.

IV. Discussion

A. Discussing findings

This study aimed to explore the applications of individual power metrics for performance monitoring in wheelchair basketball athletes. Results show that power profiles are dependent on classification, thus creating possibilities for individual performance monitoring. One way for individual performance monitoring can be done with power profiles for long-term monitoring. Game performance can be compared to previous games as well as average and maximum performance of an individual athlete's career or season.

In the consecutive power profiles, the spread of the values is not substantial, meaning that they do not deviate significantly from the mean. In contrast, the arranged power profiles exhibit more outliers. This allows the arranged power profile to highlight how an athlete's sprint performance in specific pushes compares to standard performance. For instance, if an athlete produces more power in sprint push 4 and less in sprint push 5 compared to the mean, this indicates a variation in the sprinting pattern. Analyzing these variations in combination with play style can provide insights into how different play styles impact sprint power distribution. Additionally, changes in sprint power distribution can reflect the demands of different player positions, offering valuable information when an athlete changes positions.

However, a downside of the arranged power profile is that it is less suitable for long-term performance monitoring because it is influenced by play style and position. For this purpose, a metric less affected by these factors is preferred. The consecutive power profile is less impacted by play style and position, making it better suited for long-term performance monitoring.

While both power profiles have their uses, the consecutive power profile is the best representation of performance. This is because the arranged power profile is mainly correlated with a value from the consecutive power profile rather than values from its own power profile. Additionally, the consecutive power profile is more intuitive, as more pushes in a sprint will naturally show a reduction in power output. The arranged power profile, with its greater spread, is less useful for detecting anomalies.

The amount of work done by the athletes can provide information about the demands of the current game. If an athlete does less work in a quarter than the quarter before, it could indicate that the athlete is fatigued. However, work done can also be used to prevent fatigue by monitoring the work done during a game. If an athlete produces more work than desired, the coach can give that athlete more rest to recover.

Work done can give direct insight into the effort of the athletes during a game. Power profiles give insight into the game's performance after the game has finished. Both metrics can be tailored to every individual athlete and provide meaningful information to coaches to get a better understanding of the demands of the game and the individual performance of the athlete. Results indicate that higher-classified athletes produce more power than lower-classified athletes. However, more research needs to be done with more athletes to verify if this applies to all athletes.

The rolling resistance and resistance forces are similar to the ones reported during treadmill and overground wheelchair propulsion by Rietveld et al. (2021) and Mason et al. (2013), except for one athlete. The athlete with classification 4.5 had a higher rolling coefficient and therefore higher rolling resistance than previously reported in these studies. Figure 12 shows the coasting test velocity and fitted lines of that athlete. No abnormalities are found in this data. Therefore the higher rolling coefficient could be attributed to other factors, such as tire pressure, or this athlete has an inherently higher rolling coefficient. It is important to note that only one coasting test was performed, so there is no additional test data available to verify these findings. The power values of the pushes are similar to the ones reported by Janssen et al. (submitted).

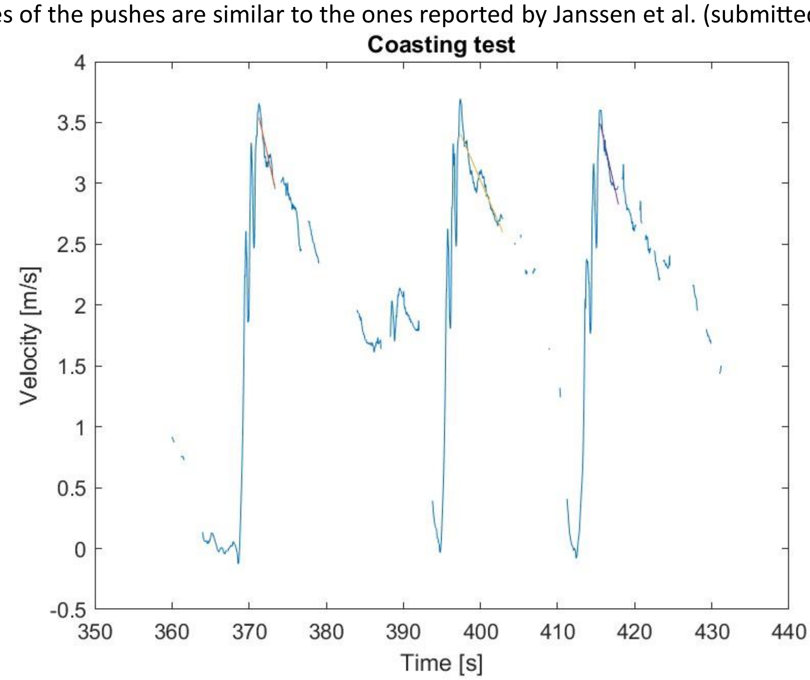


Fig. 12: Coasting test of the athlete with classification 4.5 with fitted lines (only straight line data are plotted), the blue line represents the velocity of the wheelchair and athlete. The other colored lines are the first-order polynomials

B. Limitations

One of the largest limitations of this study is that it only considers straight-line power. However, concerning the power profiles this should not affect the results, since the higher power values are most certainly produced during straight-line sprints. This study focused on sprint power, therefore the work done can also be described as sprint/anaerobic work and is consequently not affected by using only straight-line sprints. However to increase the usage of work done, mainly aerobic work done, in wheelchair basketball, one can look at corners for a better understanding of fatigue. Another limitation of this study is that the rolling resistance was calculated once and assumed to be equal for all games. However, some factors may influence the rolling resistance, for example, tire pressure or wheel angle. However, if kept the same the rolling resistance coefficient could be constant. On the other hand, Heringa (2023) showed a model that can calculate the normal force distribution and therefore detect trunk motion and improve the friction forces' power calculations. On that note, trunk motion was not taken into account in this current study, research by Dijk et al. (2024a) showed that disregarding trunk motion results in a 1-6% underestimation of power depending on the amount of trunk motion possible. Since this study's main focus was on differences within the athlete and displays of power of a single athlete, this has affected the results of this study. Consequently, when future studies are comparing different classifications, trunk motion needs to be taken into account.

C. Future research

Future research can focus on using the limitations mentioned in this paper. However, it can also look at using heart rate together with power. In a study by Sanders et al. (2017a) they mention that combining power and heart rate will result in a good estimate of fatigue. They also mention using session rating of perceived exertion (sRPE) with power. So a ratio between sRPE and work done might be useful for long-term fatigue monitoring and preventing overtraining or injury. Although this was done in an endurance sport, further research can study if it is useful in wheelchair basketball. Different positions were also not investigated in this study, further research can be done if positions play a role in power profiles or work done. To verify the results of this study and for future research, it should be noted that a higher sample size is recommended.

V. Conclusion

Power profiles and work done can give insight into an athlete's individual performance over time and during a game. This can improve the understanding of wheelchair basketball players' performance and be useful for coaches and trainers. Future studies can improve the suggested metrics by incorporating trunk motion and cornering.

References

Allen, H., Coggan, A., & McGregor, S. (2019). *Training and racing with a power meter*. VeloPress. https://books.google.nl/books?id=-pJutgEACAAJ

Barbosa, T., Forte, P., Morais, J., & Coelho, E. (2014). Partial contribution of rolling friction and drag force to total resistance of an elite wheelchair athlete.

Barker, A., Bond, B., Toman, C., Williams, C., & Armstrong, N. (2011). Critical power in adolescents: Physiological bases and assessment using all-out exercise. *European journal of applied physiology*, *112*, 1359–70. https://doi.org/10.1007/s00421-011-2088-8

Byrnes, D., Hedrick, B., Byrnes, D., & Shaver, L. (1994). Comprehensive basketball grading system. *Wheelchair basketball*, 79.

Chenier, F., Pelland-Leblanc, J.-P., Parrinello, A., Marquis, E., & Rancourt, D. (2021). A high sample rate, wireless instrumented´ wheel for measuring 3d pushrim kinetics of a racing wheelchair. *Medical Engineering & Physics*, *87*, 30–37. https://doi.org/10.1016/j.medengphy.2020.11.008

Coutts, K. (1992). Dynamics of wheelchair basketball. *Medicine and science in sports and exercise*, *24*(2), 231–234. http://europepmc.org/abstract/MED/1532225

Croft, L., Dybrus, S., Lenton, J., & Goosey-Tolfrey, V. (2010). A comparison of the physiological demands of wheelchair basketball and wheelchair tennis. *International Journal of Sports Physiology and Performance*, *5*(3), 301–315. https://doi.org/10.1123/ijspp.5.3.301 de Vette, V., Veeger, D., & Dijk, M. (2022). Using wearable sensors to estimate mechanical power output in cyclical sports other than cycling—a review. *Sensors*, *23*, 50. https://doi.org/10.3390/s23010050

Erp, T., Hoozemans, M., Foster, C., & de Koning, J. (2019). The influence of exercise intensity on the association between kj spent and various training loads in professional cycling. *International Journal of Sports Physiology and Performance*, *14*, 1–20. https://doi.org/10.1123/ijspp.2018-0877

Gløersen, Ø., Losnegard, T., Malthe-Sørenssen, A., Dysthe, D., & Gilgien, M. (2018). Propulsive power in cross-country skiing: Application and limitations of a novel wearable sensor-based method during roller skiing. *Frontiers in Physiology*, *9*. https://doi.org/10.3389/fphys.2018.01631

Halson, S. (2014). Monitoring training load to understand fatigue in athletes. *Sports medicine (Auckland, N.Z.)*, *44*. https://doi.org/10.1007/s40279-014-0253-z

Heringa, L. (2023, February). *Using inertial sensors to estimate the normal force on the castor wheels during handrim wheelchair propulsion in-field* [Available at http://resolver.tudelft.nl/uuid:2b690cae-759d-4921-a98b-cb1563741114].

Holt, A., Hopkins, W., Aughey, R., Siegel, R., Rouillard, V., & Ball, K. (2021). Concurrent validity of power from three on-water rowing instrumentation systems and a concept2 ergometer. *Frontiers in Physiology*, *12*, 758015. https://doi.org/10.3389/fphys.2021.758015

IWBF. (n.d.). History of wheelchair basketball (IWBF, Ed.) [[Online]]. https://iwbf.org/the-game/history-wheelchair-basketball/

Janssen, R., van Dijk, M., Rietveld, T., de Groot, S., van der Woude, L., Houdijk, H., & Vegter, R. (submitted). The combined strength of standardized lab sprint testing and wheelchair mobility field testing among wheelchair tennis players.

Leo, P., Spragg, J., Podlogar, T., Lawley, J., & Mujika, I. (2022). Power profiling and the power-duration relationship in cycling: A narrative review. *European Journal of Applied Physiology*, *122*. https://doi.org/10.1007/s00421-021-04833-y

Mason, B., Lenton, J., Leicht, C., & Goosey-Tolfrey, V. (2013). A physiological and biomechanical comparison of over-ground, treadmill and ergometer wheelchair propulsion. *Journal of sports sciences*, *32*. https://doi.org/10.1080/02640414.2013.807350

Miyazaki, Y., Iida, K., Nakashima, M., Maruyama, T., & Yamanobe, K. (2020). Measurement of push-rim forces during racing wheelchair propulsion using a novel attachable force sensor system. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, *0*(0). https://doi.org/10.1177/1754337120904260

Molik, B., Laskin, J., Kosmol, A., Skucas, K., & Bida, U. (2010). Relationship between functional classification levels andˇ anaerobic performance of wheelchair basketball athletes. *Research quarterly for exercise and sport*, *81*, 69–73. https://doi.org/10.1080/02701367.2010.10599629

Mujika, I. (2016). Quantification of training and competition loads in endurance sports: Methods and applications. *International Journal of Sports Physiology and Performance*, *12*, 1–25. https://doi.org/10.1123/ijspp.2016-0403

Paulson, T., Mason, B., Rhodes, J., & Goosey-Tolfrey, V. (2015). Individualized internal and external training load relationships in elite wheelchair rugby players. *Frontiers in Physiology*, *6*, 1–7. https://doi.org/10.3389/fphys.2015.00388

Pelland-Leblanc, J.-P., Martel, F., Langelier, E., Smeesters, C., Berrigan, F., Laroche, J., & Rancourt, D. (2013). Instantaneous power measurement in wheelchair racing.

Pinot, J., & Grappe, F. (2011). The record power profile to assess performance in elite cyclists. *International journal of sports medicine*, *32*, 839–44. https://doi.org/10.1055/s-0031-1279773

Rhodes, J. M., Mason, B. S., Malone, L. A., & Goosey-Tolfrey, V. L. (2015). Effect of team rank and player classification on activity profiles of elite wheelchair rugby players. *Journal of sports sciences*, *33*(19), 2070–2078.

Rietveld, T., Mason, B., Goosey-Tolfrey, V., Woude, L., Groot, S., & Vegter, R. (2021). Inertial measurement units to estimate drag forces and power output during standardised wheelchair tennis coast-down and sprint tests. *Sports biomechanics*, 1–19. https://doi.org/10.1080/14763141.2021.1902555

Sanders, D., Abt, G., Hesselink, M., Myers, T., & Akubat, I. (2017b). Methods of monitoring training load and their relationships to changes in fitness and performance in competitive road cyclists. *International journal of sports physiology and performance*, *12*. https://doi.org/10.1123/IJSPP.2016-0454

Sanders, D., Heijboer, M., Hesselink, M., Myers, T., & Akubat, I. (2017a). Analysing a cycling grand tour: Can we monitor fatigue with intensity or load ratios? *Journal of Sports Sciences*, *36*, 1–7. https://doi.org/10.1080/02640414.2017. 1388669

Sarro, K. J., Misuta, M. S., Burkett, B., Malone, L. A., & Barros, R. M. (2010). Tracking of wheelchair rugby players in the 2008 demolition derby final. *Journal of sports sciences*, *28*(2), 193–200.

Soligard, T., Schwellnus, M., Alonso, J., Bahr, R., Clarsen, B., Dijkstra, P., Gabbett, T., Gleeson, M., Hagglund, M., Hutchinson,¨ M., Janse van Rensburg, D. C., Khan, K., Meeusen, R., Orchard, J., Pluim, B., Raftery, M., Budgett, R., & Engebretsen, L. (2016). How much is too much? (part 1) international olympic committee consensus statement on load in sport and risk of injury. *British Journal of Sports Medicine*, *50*, 1030–1041. https://doi.org/10.1136/bjsports-2016-096581

Sørensen, A., Aune, T. K., Rangul, V., & Dalen, T. (2019). The validity of functional threshold power and maximal oxygen uptake for cycling performance in moderately trained cyclists. *Sports*, *7*, 217. https://doi.org/10.3390/sports7100217

Uddin, M. Z., Seeberg, T., Kocbach, J., Liverud, A., Gonzalez, V., Sandbakk, O., & Meyer, F. (2021). Estimation of mechanical power output employing deep learning on inertial measurement data in roller ski skating. *Sensors*, *21*, 6500. https: //doi.org/10.3390/s21196500

Usma-Alvarez, C. C., Chua, J. J. C., Fuss, F. K., Subic, A., & Burton, M. (2010). Advanced performance analysis of the illinois agility test based on the tangential velocity and turning radius in wheelchair rugby athletes. *Sports Technology*, *3*(3), 204–214.

Van der Kruk, E., van der Helm, F., Veeger, D., & Schwab, A. (2018). Power in sports: A literature review on the application, assumptions, and terminology of mechanical power in sport research. *Journal of Biomechanics*, *79*. https://doi.org/10. 1016/j.jbiomech.2018.08.031

Van der Slikke, R., Berger, M., Bregman, D., Lagerberg, A., & Veeger, D. (2015). Opportunities for measuring wheelchair kinematics in match settings; reliability of a three inertial sensor configuration. *Journal of Biomechanics*, *48*, 3398– 3405. https://doi.org/10.1016/j.jbiomech.2015.06.001

Van der Slikke, R., Berger, M., Bregman, D., & Veeger, D. (2016). Push characteristics in wheelchair court sport sprinting. *Procedia Engineering*, *147*. https://doi.org/10.1016/j.proeng.2016.06.265

Van der Slikke, R., Mason, B., Berger, M., & Goosey-Tolfrey, V. (2017). Speed profiles in wheelchair court sports; comparison of two methods for measuring wheelchair mobility performance. *Journal of Biomechanics*, *65*. https://doi.org/10. 1016/j.jbiomech.2017.10.040

Van der Slikke, R., Sindall, P., Goosey-Tolfrey, V., & Mason, B. (2022). Load and performance monitoring in wheelchair court sports: A narrative review of the use of technology and practical recommendations.: Load performance monitoring in wheelchair court sports. European Journal of Sport Science, 23, 1–33. https://doi.org/10.1080/17461391.2021.2025267

van der Slikke, R., Berger, M., Bregman, D., & Veeger, H. (2016). From big data to rich data: The key features of athlete wheelchair mobility performance. Journal of Biomechanics, 49(14), 3340–3346. https://doi.org/https://doi.org/10. 1016/j.jbiomech.2016.08.022

van Dijk, M., Hoozemans, M., Berger, M., & Veeger, D. (2024a). Trunk motion influences mechanical power estimates during wheelchair propulsion. Journal of Biomechanics, 163, 111927. https://doi.org/10.1016/j.jbiomech.2024.111927

van Dijk, M., Hoozemans, M., Berger, M., & Veeger, D. (2024b). From theory to practice: Monitoring mechanical power output during wheelchair field and court sports using inertial measurement units. Journal of Biomechanics, 166, 112052. https://doi.org/10.1016/j.jbiomech.2024.112052

van Dijk, M., Van der Slikke, R., Rupf, R., Hoozemans, M., Berger, M., & Veeger, D. (2021). Obtaining wheelchair kinematics with one sensor only? the trade-off between number of inertial sensors and accuracy for measuring wheelchair mobility performance in sports. Journal of Biomechanics, 130, 110879. https://doi.org/10.1016/j.jbiomech.2021.110879

Veeger, T., de Witte, A., Berger, M., Van der Slikke, R., Veeger, D., & Hoozemans, M. (2017). Improving mobility performance in wheelchair basketball. Journal of Sport Rehabilitation, 28, 1–26. https://doi.org/10.1123/jsr.2017-0142

Waldron, M., Gray, A., Furlan, N., & Murphy, A. (2015). Predicting the sprint performance of adolescent track-cyclists using the three-min all-out test. Journal of Strength and Conditioning Research, 30, 1. https://doi .org/10.1519/JSC.0000000000001311