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EFFECTS OF THE FLYING START ON ESTIMATED SHORT SPRINT PROFILES USING TIMING GATES

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UTICAJ LETEĆEG STARTA NA PROCENU PROFILA KRATKIH SPRINTEVA PRIMENOM FOTO ĆELIJA

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EFFECTS OF THE FLYING START ON ESTIMATED SHORT SPRINT PROFILES USING TIMING GATES

Abstract

Short sprints are predominantly assessed using timing gates and analyzed through parameters of the *mono-exponential* equation, including estimated *maximal sprinting speed* (MSS) and *relative acceleration* (TAU), and derived *maximum acceleration* (MAC) and *relative propulsive maximal* power (PMAX), further referred to as the *No Correction* model. However, the frequently recommended flying start technique introduces a bias during parameter estimation. To correct this, two additional models (*Estimated TC* and *Estimated FD*) were proposed, and a two-part study was conducted to estimate model precision and sensitivity. In the first part, simulation was used to compare estimated and actual parameters under different flying start conditions. In the second part, 31 basketball players executed 30-meter sprints. Parameters were estimated using a laser gun, representing the *criterion* measure, and five different timing gate models, representing the *practical* measures. The simulation study demonstrated that the two proposed models provided more precise estimates using the *percent difference* ($\%Diff$) estimator (median $\%Diff$ across all flying distances and parameters between -3 and 3%). Surprisingly, the *No Correction* model provided higher sensitivity, estimated using the *minimum detectable change* estimator ($\%MDC_{95}$) for MAC and TAU parameters ($\%MDC_{95}$ <5%). In the second study, only the MSS parameter demonstrated high agreement between laser gun and timing gate estimates, using the *percent mean absolute difference* (%MAD) estimator (%MAD < 10%). The MSS parameter also showed the highest sensitivity, with $\%MDC_{95}$ <17%. Interestingly, sensitivity was the highest for the *No Correction* model ($\%MDC_{95}$ <7%.). All other parameters and models demonstrated an unsatisfying level of sensitivity. Practitioners should be wary of using timing gates to estimate maximum acceleration indices and changes in their respective levels.

Keywords: sprint profiling, acceleration-velocity profile, timing-gates, laser gun, measurement, sport

Scientific field: Physical Education and Sport
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UTICAJ LETEĆEG STARTA NA PROCENU PROFILA KRATKIH SPRINTEVA PRIMENOM FOTO ĆELIJA

Sažetak

Kratki sprintevi se pretežno procenjuju koristeći foto ćelije i analiziraju se putem parametara *mono-eksponencijalne* jednačine, uključujući procenjenu *maksimalnu brzinu sprinta* (MSS) i *relativno ubrzanje* (TAU), kao i izvedenu *maksimalnu akceleraciju* (MAC) i *relativnu propulzivnu maksimalnu snagu* (PMAX), dalje nazvanih model „Bez Korekcije". Međutim, često preporučena tehnika letećeg starta uvodi grešku tokom procene parametara. Da bi se ovo ispravilo, predložena su dva dodatna modela („Procenjeni TC" i „Procenjeni FD"), a sprovedena je dvodelna studija radi procene preciznosti i osetljivosti modela. U prvom delu, simulacija je korišćena za poređenje procenjenih i stvarnih parametara pod različitim uslovima letećeg starta. U drugom delu, 31 košarkaša su izveli sprinteve na 30 metara. Parametri su procenjeni korišćenjem laserskog pištolja kao kriterijumske mere i pet različitih modela foto ćelija kao praktičnih mera. Studija simulacije je pokazala da su dva predložena modela pružila preciznije procene koristeći estimator *procentualne razlike* (%$Diff$) (medijana %$Diff$ za sve udaljenosti letećeg starta i parametre iznosila je između -3 i 3%). Iznenadjujuće, model „Bez Korekcije" je pružio veću osetljivost, procenjenu koristeći estimator *minimalne detektabilne promene* (%MDC_{95}) za parametre MAC i TAU (*%MDC_{95}* <5%). U drugoj studiji, samo parametar MSS je pokazao visoku saglasnost između procene laserskim pištoljem i procene foto ćelijama, koristeći estimator *procentualne srednje apsolutne razlike* (%MAD) (%MAD < 10%). Parametar MSS je takođe pokazao najveću osetljivost, sa %MDC_{95} <17%. Interesantno, osetljivost je bila najviša za model „Bez Korekcije" (%MDC_{95} <7%). Svi ostali parametri i modeli su pokazali nezadovoljavajući nivo osetljivosti. Praktičari bi trebalo da budu oprezni prilikom korišćenja foto ćelija za procenu maksimalne akceleracije i njene promene.

Ključne reči: sprint profilisanje, profil ubrzanje-brzina, foto ćelije, laserski pištolj, merenje, sport

Naučna oblast: Fizičko vaspitanje i sport
Uža naučna oblast: Nauke fizičkog vaspitanja, sporta i rekreacije
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1 INTRODUCTION

The physical attribute of sprint speed is widely recognized and esteemed in sports. Short sprints in most team sports, such as soccer, basketball, field hockey, and handball, are characterized by maximal sprinting from a stationary position over a distance that does not lead to deceleration upon completion. According to Mangine et al. (2014), the highest level of anaerobic power is achieved within the initial five seconds of maximal exertion. Nevertheless, the ability to achieve maximum sprint velocity varies depending on the athlete and the sport. As per the research conducted by Ward-Smith (2001), it has been observed that sprinters in track and field tend to attain their maximum speed towards the end of the race, specifically between 50-60 meters. On the other hand, Brown et al. (2004) suggest that team sports athletes reach their maximum speed much earlier in the race, typically between 30-40 meters. The assessment of short sprint performance is commonly incorporated into a battery of physical fitness assessments for a diverse range of sports, irrespective of the dissimilarities in kinematics among athletes.

Force plates and 3D cameras are widely considered the gold-standard method for evaluating the mechanical characteristics of sprinting. However, obtaining a complete sprint profile poses practical and financial challenges (Morin et al., 2019; Samozino et al., 2016). The utilization of laboratory-grade methods, such as radar and laser technology, is a common practice in various studies (Buchheit et al., 2014; Edwards et al., 2020; Jiménez-Reyes et al., 2018; Marcote-Pequeño et al., 2019). However, these methods are generally not accessible to sports practitioners.

Undoubtedly, timing gates are the most commonly utilized approach for assessing sprint performance. It is common practice to position several gates at varying intervals to record split times, such as 10, 20, 30, and 40 meters. These split times can be integrated into calculating sprint mechanical characteristics, as Morin et al. (2019) and Samozino et al. (2016) proposed. The utilization of estimated sprint mechanical characteristics by practitioners can serve the purpose of elucidating individual differences, quantifying the impact of training interventions, and enhancing comprehension of the constraining factors of performance, thereby conferring a benefit upon this approach.

1.1 Mathematical model

The mono-exponential equation for velocity as a function of time has been employed in modeling short sprints. The concept was initially introduced by Furusawa et al. (1927) and subsequently gained wider recognition through the works of Samozino et al. (2016) and Clark et al. (2017). Equation 1 is utilized to determine the instantaneous horizontal velocity denoted as v, which is dependent on the time variable denoted as t, as well as two distinct model parameters.

$$v(t) = MSS \times \left(1 - e^{-\frac{t}{TAU}}\right) \qquad (1)$$

The parameters of Equation 1 are the *Maximum Sprinting Speed* (MSS), which is measured in meters per second (ms^{-1}), and the *Relative Acceleration* (TAU), which is measured in seconds (s). The parameter TAU denotes the quotient obtained by dividing the MSS by the initial

Maximum Acceleration (MAC), which is expressed in units of meters per second squared (ms^{-2}) and can be represented by Equation 2. It should be noted that TAU represents the duration needed to attain a velocity equivalent to 63.2% of the MSS, as determined by the given Equation 1.

$$MAC = \frac{MSS}{TAU} \qquad (2)$$

While TAU is a parameter employed in the equations and subsequently estimated, it is advisable to employ and report MAC as it is more straightforward to comprehend, particularly for professionals and trainers.

The equation pertaining to the horizontal acceleration, as denoted by Equation 3, can be obtained through the derivation of Equation 1.

$$a(t) = \frac{MSS}{TAU} \times e^{-\frac{t}{TAU}} \qquad (3)$$

The equation for distance covered (Equation 4) can be derived by means of integrating Equation 1.

$$d(t) = MSS \times \left(t + TAU \times e^{-\frac{t}{TAU}}\right) - MSS \times TAU \qquad (4)$$

Figure 1 presents a visual representation of the sprint kinematics of four hypothetical athletes who possess varying values of MSS and MAC parameters. When velocity is plotted against acceleration for the four hypothetical athletes, given Equation 1, a *linear relationship* can be observed, as illustrated in Figure 2. This model's feature facilitates the process of *simplification*, which involves generating an aggregated summary of the short sprint kinematics through the utilization of two descriptive parameters, namely, MSS and MAC. The nomenclature employed to describe the aforementioned relationship (Figure 2) is known as the *Acceleration-Velocity Profile* (AVP).

The Acceleration-Velocity Profile (i.e., the MSS and MAC parameters), can thus serve as a model or representation of two of the three prevalent *phenomenological* characteristics in sprinting (Debaere et al., 2013; T. Haugen et al., 2019; Healy et al., 2022; Mero et al., 1992; Ross et al., 2001; Volkov & Lapin, 1979). These include (1) the ability to achieve maximum forward acceleration (represented with the MAC parameter), (2) the ability to attain maximum speed (represented with the MSS parameter), and (3) ability to sustain speed while resisting the onset of fatigue (which is not a factor in short sprint performance as there is no deceleration involved).

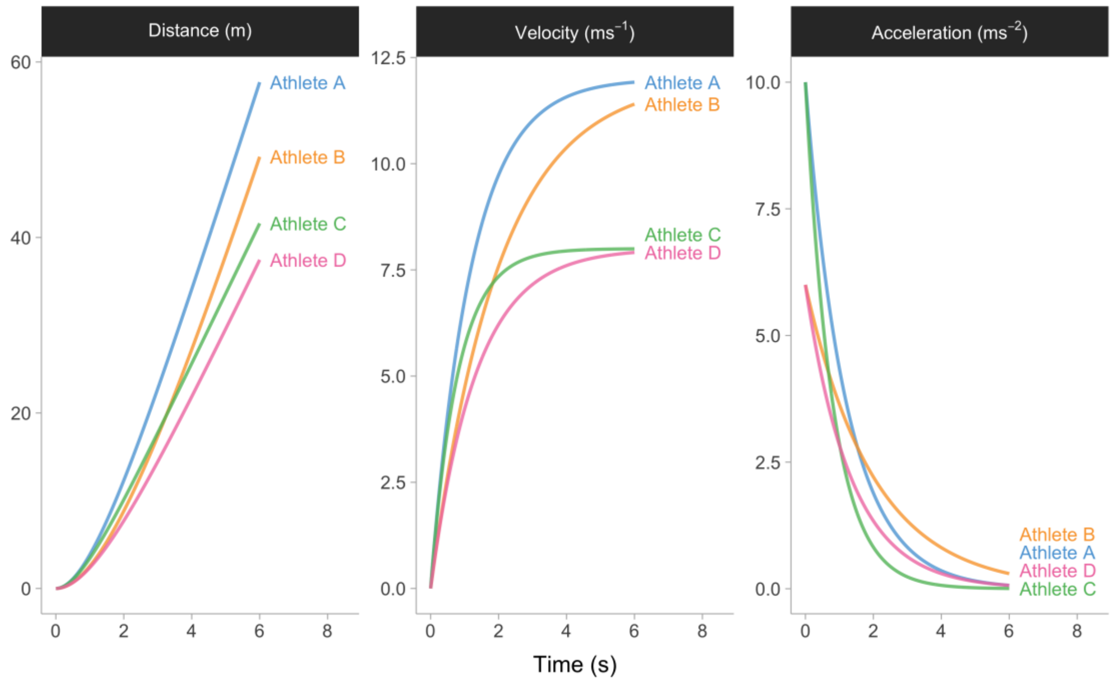


Figure 1. *Four athletes with different maximum sprinting speed (MSS) and maximum acceleration (MAC) parameters.*

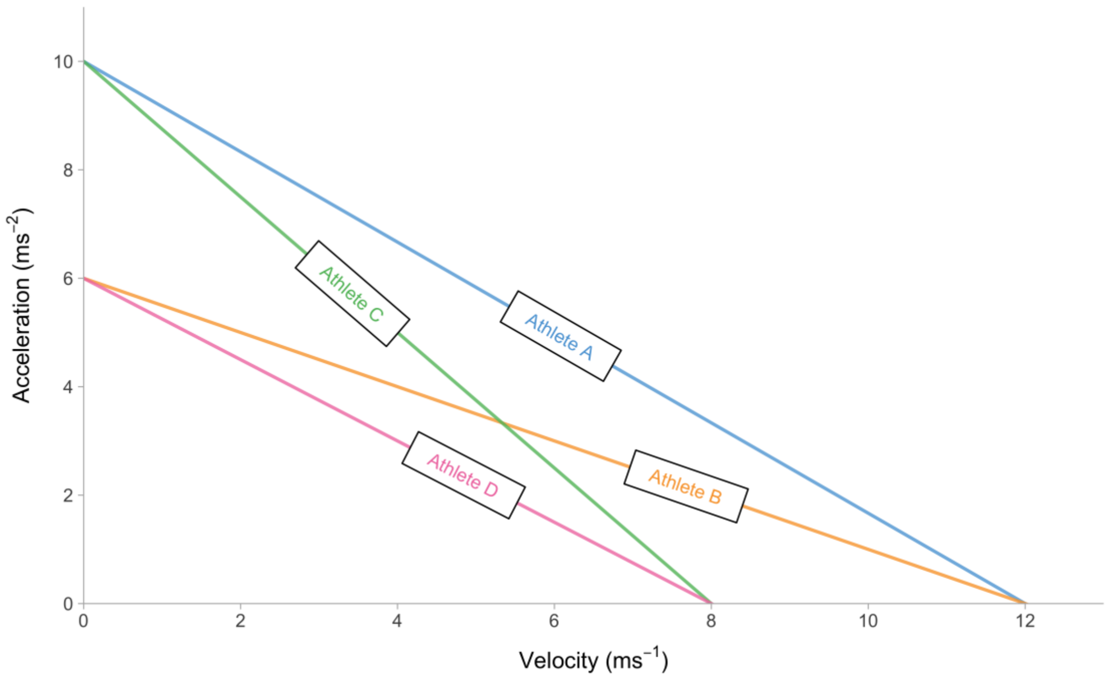


Figure 2. *The linear relationship between velocity and acceleration, given the mono-exponential Equation 1, for four hypothetical athletes. This descriptive profile is termed the Acceleration-Velocity Profile (AVP).*

1.2 Model parameters estimation using laser/radar gun

The problem related to estimating model parameters using a laser/radar gun could be illustrated through a simple example. The data presented in Figure 3 pertains to the velocity of a standing start 30 m short sprint over time. The data was collected using a laser gun (CMP3 Distance Sensor, Noptel Oy, Oulu, Finland) and was sampled at a rate of 2.56 KHz. A polynomial function modeling the relationship between distance and time was employed and subsequently resampled at a frequency of 1,000 Hz using Musclelab™ v10.232.107.5298, a software developed by Ergotest Technology AS located in Langesund, Norway. As illustrated in Figure 3, Musclelab™ provides measurements for both unprocessed velocity (*Raw* velocity in Figure 3), and processed velocity (*Smoothed* velocity in Figure 3). The specific technique used for filtering and smoothing is confidential information of Ergotest Technology AS).

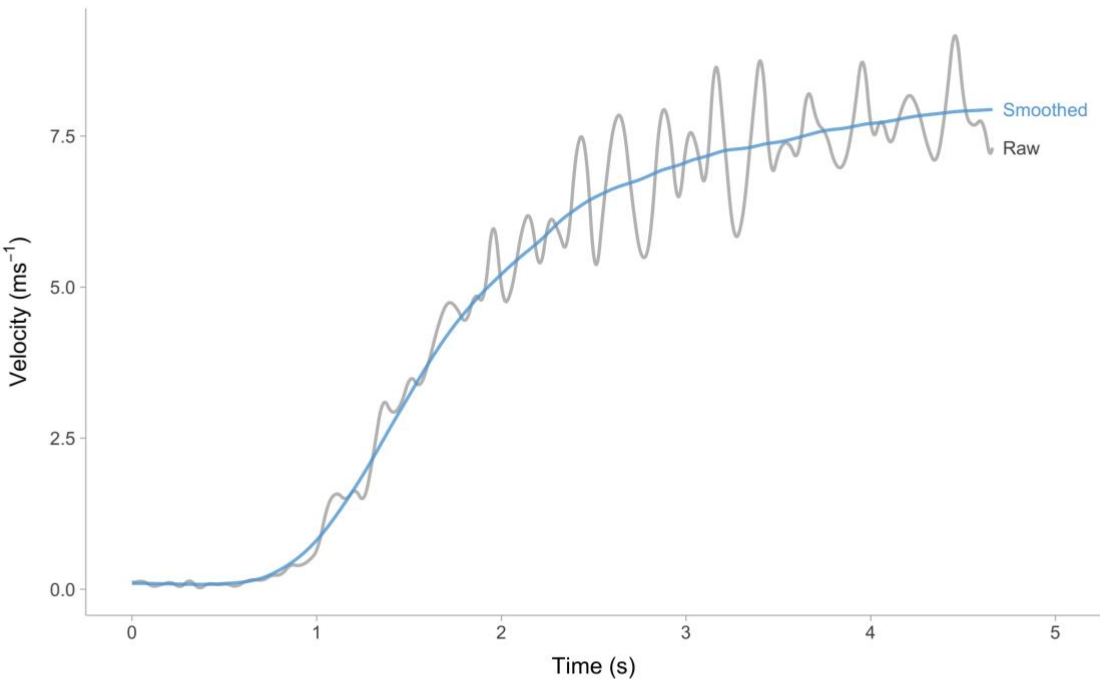


Figure 3. *Sample laser gun (Musclelab™ LaserSpeed, Ergotest Technology AS, Langesund, Norway) output during 30 m sprint. The grey line indicates raw velocity (sampled at 1,000 Hz). The blue line indicates smoothed velocity (the exact filtering/smoothing method is a proprietary secret of the Ergotest Technology AS)*

As evidenced by the data presented in Figure 3, the initiation of the sprint does not occur at the onset of the time interval ($t = 0\ s$). Therefore, it is crucial to trim the data that comes before the sprint itself. One possible approach is to apply a filter to the velocity data, specifically targeting values that exceed a predetermined threshold, such as 0.5 ms^{-1}. Furthermore, it is imperative to adjust Equation 1 by introducing an additional parameter for estimation, namely *time-correction* (TC) (Equation 5). The TC parameter functions as an *intercept* in the model, enabling it to make adjustments in both directions and to make predictions regarding the onset of sprinting.

$$v(t) = MSS \times \left(1 - e^{-\frac{t+TC}{TAU}}\right) \qquad (5)$$

The process of determining parameters, specifically MSS, TAU, and TC, as denoted in Equation 5, is accomplished through the utilization of *non-linear least squares regression*. Researchers, coaches, and sports scientists have utilized the built-in solver function of Microsoft Excel (Microsoft Corporation, Redmond, Washington, United States) to conduct short sprint modeling (Clark et al., 2017; Morin, 2017; Morin et al., 2019; Morin & Samozino, 2019; Samozino et al., 2016; Stenroth et al., 2020; Stenroth & Vartiainen, 2020). The open-source package **{shorts}** for R-language (R Core Team, 2022), has recently incorporated various functionalities, along with supplementary features (Jovanović, 2023; Jovanović & Vescovi, 2022). The package employs the nlsLM() function from the **{minpack.lm}** package (Elzhov et al., 2023) for estimating model parameters using non-linear least squares regression. In contrast to the solver function integrated within Microsoft Excel, the **{shorts}** package offers a more feature-rich, flexible, transparent, and reproducible environment framework for constructing models of short sprints. Accordingly, this study will employ the **{shorts}** package to compute model parameters.

The estimated values of MSS, TAU, MAC, and TC parameters were obtained from the sample provided in Figure 3. The estimated values for MSS, TAU, MAC, and TC were found to be 8.16 ms^{-1}, 1.03 s, 7.9 ms^{-2}, and -0.92 s, respectively. Figure 4 illustrates the adjusted mono-exponential model's (represented by Equation 5) predictions (indicated by the red line) in comparison to the data collected from the laser gun.

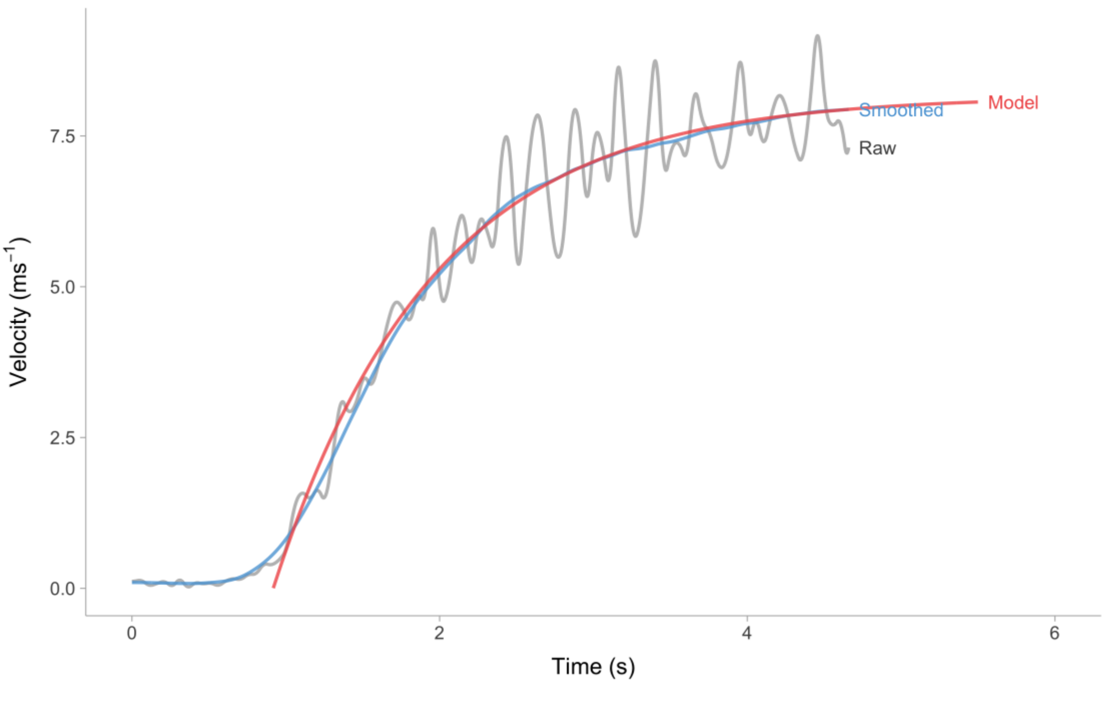


Figure 4*. Modified mono-exponential model (Equation 5) applied to the raw velocity of the sample Laser gun sample (Figure 3). The grey line indicates raw velocity (sampled at 1,000 Hz). The blue line indicates smoothed velocity (the exact filtering/smoothing method is a proprietary secret of the Ergotest Technology AS). The red line represents the mono-exponential model prediction*

The computation of acceleration can be achieved through the utilization of both *smoothed* and *model-predicted* velocity, employing the $\bar{a} = \frac{\Delta v}{\Delta t}$ methodology. Figure 5 depicts the relationship between velocity and acceleration through the utilization of both *smoothed* and *model-predicted* velocity. Figure 5 illustrates a notable inconsistency between the *smoothed* and *model-predicted* data. This discrepancy arises due to the assumption made by the mono-exponential model, which considers the maximum acceleration to occur when the velocity is zero. The utilization of a standing start instead of a block start is the likely reason for the deviation from the aforementioned assumption in the method that employs *smoothed* observed velocity.

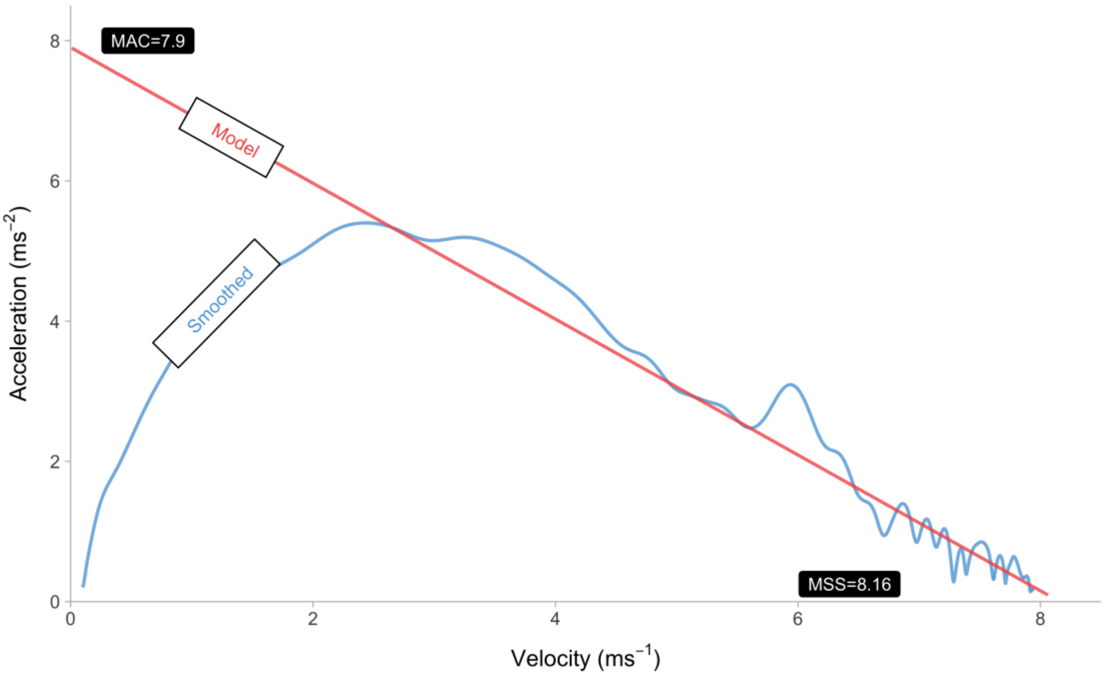


Figure 5*. Acceleration-Velocity trace using smoothed and model-predicted velocities from Figure 4. Acceleration for every sample is estimated using $\bar{a} = \frac{\Delta v}{\Delta t}$. Estimated maximum sprinting speed (MSS) and maximum acceleration (MAC) parameters are written close to the x- and y-axes*

It is important to emphasize that all three velocities (i.e., *raw*, *smoothed*, and *model-predicted*) represent approximations of much more complex short sprint performance [1]. *Raw* velocity is the velocity estimated from the body point closest to the laser gun, and that is often the low back of the athlete since the laser was positioned approximately 1 *m* from the ground. As previously stated in the Introduction, force plates, and 3D cameras are widely recognized as the preferred methods for evaluating the mechanical characteristics of sprinting, specifically

[1] The distinction between the *Small World* models and *Large World*. The concept of the Small world refers to the self-contained and internally consistent world of a given model, whereas the Large world pertains to the wider context in which the model is applied (Binmore, 2011; Gigerenzer et al., 2015; McElreath, 2020; Savage, 1972; Volz & Gigerenzer, 2012).

in terms of estimating the velocity of the *center-of-mass* (COM). Therefore, radar and laser may be regarded as the *silver* standard, while the *raw* velocity can be seen as the most accurate estimate of the COM velocity.

The velocity that has been *smoothed* refers to the velocity that has been averaged over steps (i.e., *step-averaged* velocity), without taking into account the acceleration and deceleration that is evident in the *raw* velocity as depicted in Figure 3. The purpose of this smoothing is to simplify the analysis of kinematics. The mono-exponential model, encompassing both Equation 1 and Equation 5, provides a simplified approach to analyzing short sprint kinematic performance. This model utilizes two variables, namely MSS and MAC, to describe and consolidate the short sprint performance. The simplification in question is highly practical, as it facilitates the comparison of athletes and enables the monitoring of changes in training interventions. However, it is important to note that this approach may yield misleading results, as illustrated in Figure 5, due to potential disparities between the *smoothed* velocity and model predictions.

1.3 Estimation of model parameters using timing gate split times

The dataset in Table 1 includes a sample of split times that were recorded during a sprint performance of 40 meters. The split timings were measured using timing gates placed at a distance of 5, 10, 20, 30, and 40 meters.

Table 1. *Measured split times over 40 meters sprint utilizing timing gates positioned at 5, 10, 20, 30, and 40 m*

Distance (m)	Split time (s)
5	1.40
10	2.13
20	3.35
30	4.46
40	5.54

The procedure for estimating model parameters using split times entails employing distance as an *independent* variable (i.e., *predictor*) and time as the *dependent* variable (i.e., *outcome*). As a result, Equation 4 is structured in the form of Equation 6.

$$t(d) = TAU \times W\left(-e^{\frac{-d}{MSS \times TAU}} - 1\right) + \frac{d}{MSS} + TAU \qquad (6)$$

The symbol W appearing in Equation 6 denotes the mathematical function known as *Lambert's W function*. This function is characterized as the inverse of the multivalued function $f(w) = we^{w}$ (Corless et al., 1996; Goerg, 2022). The use of Equation 4, where time serves as the independent variable and distance as the dependent variable, is a prevalent practice in academic research (Morin, 2017; Morin & Samozino, 2019; Stenroth & Vartiainen, 2020). It is advisable to refrain from utilizing this approach as it has the potential to generate *bias* in the estimated parameters (Motulsky, 2018, p. 341). While the bias in question may not have practical significance when it comes to profiling short sprints, it is a flawed statistical practice and should be eschewed. Therefore, it is advisable to employ statistically accurate Equation 6 for the estimation of model MSS and TAU parameters.

Based on the split times provided in Table 1, the estimated values for MSS, TAU, and MAC parameters are 9.54 ms^{-1}, 1.37 s, and 6.96 ms^{-2}, respectively. Figure 6 illustrates the predictions of Equation 6 model.

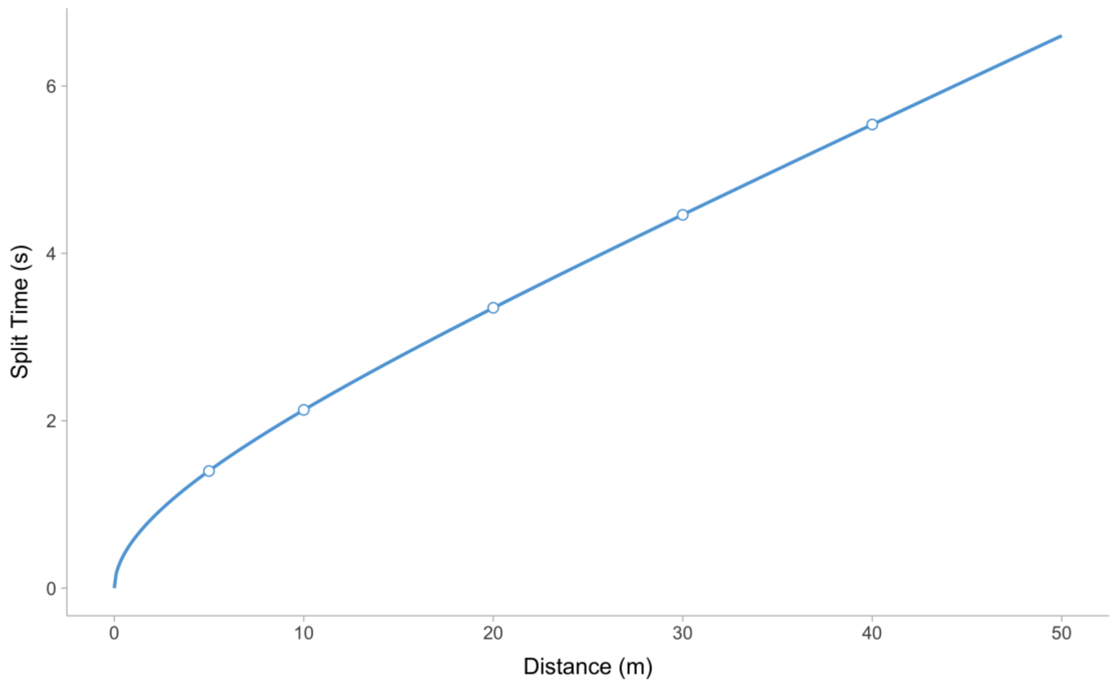


***Figure 6**. Split time predictions using Equation 6 model (depicted as a line) and observed timing gate split times from Table 1 (depicted as points)*

The parameter known as *maximal relative power* ($PMAX$), which is expressed in units of Watts per kilogram (W/kg), is frequently calculated and documented in academic literature (Morin et al., 2019; Samozino et al., 2016). The calculation of $PMAX$ is performed utilizing Equation 7. The approach employed for $PMAX$ estimation in this context does not take into account the impact of air resistance, thereby indicating the *net* or relative *propulsive* power. The $PMAX$ value was computed by utilizing the estimated MSS and MAC parameters, resulting in a value of 16.6 W/kg.

$$PMAX = \frac{MSS \times MAC}{4} \qquad (7)$$

1.4 Inaccuracies in estimated parameters using timing gates due to the flying start and reaction time

To get accurate estimates of the short sprint parameters, it is crucial to synchronize the initiation of force generation with the commencement of the sprint timing, usually known as the "first movement" trigger. This has been highlighted in various studies (Haugen et al., 2012; Haugen et al., 2019, 2020c, 2020a; T. Haugen & Buchheit, 2016a; Samozino et al., 2016). The acquisition of sprint data through timing gates poses a challenge that can significantly affect the estimated parameters.

In order to illustrate the effect, consider a hypothetical scenario involving three triplet siblings, Andrew, Ben, and Cole, who possess identical characteristics for short sprints, including MSS of 9.5 ms^{-1}, TAU of 1.36 s, MAC of 7 ms^{-2}, and $PMAX$ of 16.62 W/kg (which are indicative of authentic or *true* short sprint parameters). All three triplet siblings executed a sprint of 40 meters from a stationary position, with timing gates placed at distances of 5, 10, 20, 30, and 40 m. Andrew and Ben activate the timing system when they cross the beam at the beginning of the sprint (i.e., $d = 0\ m$). For Cole, the timing system is activated after the gunfire.

Andrew embodies the *theoretical* framework positing that the commencement of force production and the initiation of timing are in complete synchrony. The split times belonging to Andrew have already been employed in Table 1.

Conversely, Ben elects to displace himself marginally from the primary timing gate (i.e., for a flying distance of 0.5 meters) and employs *body rocking* to instigate the sprint commencement. To clarify, Ben employs a technique known as a *flying start*, frequently utilized when testing athletes in field sports. The utilization of a flying start distance is frequently suggested from a measurement standpoint to prevent untimely activation of the timing system caused by elevated knees or swinging arms. This recommendation is supported by various studies (Altmann et al., 2015, 2017, 2018; Haugen et al., 2020a; T. Haugen & Buchheit, 2016a). Flying start at the beginning of a short sprint can also be attributed to the act of body rocking during the initial standing start. It is evident that any commencement characterized by a disparity between the initial force production and the onset time has the potential to result in distorted estimated parameters. The difficulty in enhancing sprint characteristics coupled with inconsistent starts can potentially mask the impact of the training intervention or, in other words, reduce the *sensitivity* of the measurement to detect true changes.

Cole's start is set off by gunfire. Therefore, his split times include an extra response time of 0.2 s. This situation bears resemblance to a hypothetical circumstance in which an athlete inadvertently activates a timing mechanism by standing in close proximity to the initial timing gate. The data provided by Cole can be utilized to illustrate the impact of this situation on the estimated parameters.

In this hypothetical scenario, utilized timing gates offer a high level of accuracy, with measurements being recorded up to two decimal places (specifically, the nearest ten milliseconds). However, it is essential to note that this precision also introduces a potential source of inaccuracy in the measurements obtained. The sprint splits are visually depicted in Figure 7.

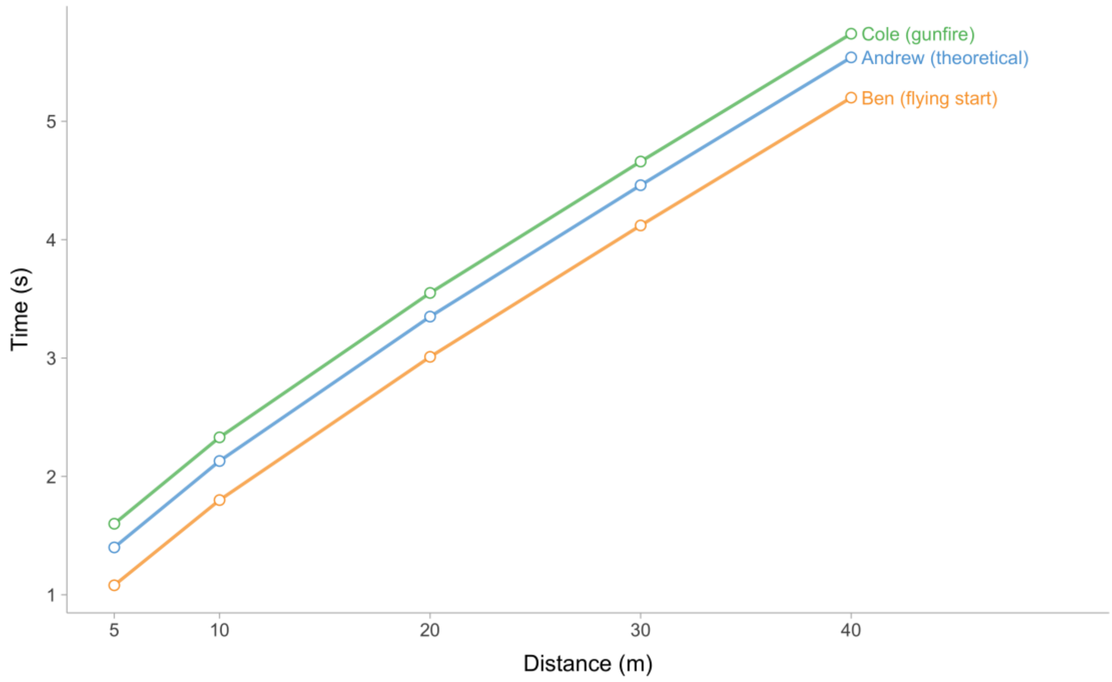


Figure 7. *Andrew, Ben, and Cole recorded their respective split timings while running 40 meters. The sprint performances of the three brothers are indistinguishable, although they employ distinct sprint beginnings, leading to variations in their split timings.*

The outcomes presented in Table 2 indicate that the estimated short sprint parameters for each of the three siblings deviate from the *true* parameters employed to produce the data, which represent their genuine short sprint characteristics. The estimated parameters of all three siblings are subject to bias owing to the precision of timing gates, which is limited to two decimal places (i.e., 10 ms). The presence of bias in the estimated parameters for Ben can be attributed to the inclusion of a flying start, whereas for Cole, the bias can be attributed to the involvement of reaction time in the split times.

Table 2. *Estimated sprint parameters for Andrew, Ben, and Cole. All three siblings exhibit equivalent sprint performance. However, they employ distinct sprint initiation techniques, leading to variations in split durations and, thus, divergent estimations of sprint parameters. The precision of the timing gates, which is accurate to two decimal places (i.e., 10 ms), resulting in estimated parameters for Andrew that deviate from the true values.* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

Athlete	MSS	TAU	MAC	PMAX
True	*9.50*	*1.36*	*7.00*	*16.62*
Andrew (theoretical)	9.54	1.37	6.96	16.60
Ben (flying start)	8.90	0.73	12.15	27.02
Cole (gunfire)	10.36	1.96	5.27	13.66

1.5 How to overcome bias in estimated parameters when using timing gates?

According to existing literature, a feasible approach to convert to "first movement" triggering while employing the suggested 0.5 m flying distance behind the initial timing gate is to apply a correction factor of +0.5 s (i.e., the addition of +0.5 s to split times) (Haugen et al., 2012; Haugen et al., 2019, 2020c; T. Haugen & Buchheit, 2016a). The study conducted by Haugen et al. (2012) revealed a noteworthy finding that the mean disparity in the 40-meter sprint time between the standing start initiated by a photocell trigger and a block start to gunfire was 0.27 seconds. As a result, it is imperative to incorporate a timing correction factor to avoid any additional imprecision in the evaluation of mechanical parameters. However, if the correction factor is too large or small, it may also lead to imprecision in mechanical parameters.

1.5.1 Estimated time correction model

Rather than relying on *apriori* time correction values from existing literature, it is possible to estimate this parameter by utilizing the provided data in conjunction with MSS and TAU. Stenroth et al. (2020) study on sprint profiling in ice hockey suggests utilizing a comparable methodology, referred to as the *time shift method*, and an estimated parameter termed the *time shift parameter*. Consistent with existing literature and utilizing the adjusted mono-exponential equation employed for laser gun data modeling (refer to Equation 5), the present study designates this parameter as *time correction* (TC).

Implementing the TC parameter in the original Equation 6 now yields the new Equation 8.

$$t(d) = TAU \times W\left(-e^{\frac{-d}{MSS \times TAU}} - 1\right) + \frac{d}{MSS} + TAU - TC \qquad (8)$$

Equation 8 is utilized as the model definition in the *Estimated time correction* (*Estimated TC*) model. The model using Equation 6 is termed the *No Correction* model throughout this study. Models in which TC is constant (i.e., by simply adding predefined TC to split times) are termed *Fixed time correction* (*Fixed TC*) models.

From a regression standpoint, the TC parameter can be interpreted as an intercept. Assuming a fixed time shift is present, such as in the case of reaction time or premature triggering of timing equipment, TC parameter can be beneficial in unbiasing estimated parameters (i.e., MSS and TAU). Comparing Andrew and Cole as presented in Figure 7, it can be observed that the lines representing their respective split times exhibit a parallel relationship. The utilization of the *Estimated TC* model in this particular scenario has the potential to mitigate bias that may exist between Andrew and Cole. In Ben's case, the utilization of the *Estimated TC* model has the potential to alleviate bias in estimated parameters as well. However, upon closer examination of Figure 7, it becomes apparent that the lines representing Ben and Andrew are non-parallel. The non-constant time shift is attributed to the pre-existing velocity at the triggering of the initial timing gate. Thus, the inclusion of the TC parameter will not completely remove the bias involved in Ben's case.

The aforementioned models, namely the *Fixed TC* models with values of +0.3 and +0.5 s, as well as the *Estimated TC* model, were utilized to analyze the split times of Andrew, Ben, and Cole. The model parameters that were estimated can be located in Table 3, alongside the parameter values that were previously estimated using the *No Correction* model. As evidenced by the data presented in Table 3, the inclusion of a +0.3 s value yielded favorable results for Ben in terms of approximating the *true* parameter values. Conversely, the incorporation of a +0.5 s value had an adverse effect on the unbiased estimation of parameters.

The *Estimated TC* model demonstrated efficacy in mitigating bias in parameter estimates across all three brothers. The estimated TC parameter for Cole exhibited a high degree of proximity to the actual reaction time of 0.2 s.

1.5.2 Estimated flying distance model

The *Estimated TC* model demonstrated favorable performance in Ben's case (sibling involving a flying start). However, rather than relying on the assumption of constant time shift to mitigate bias in the estimates, an alternative approach involves incorporating the *flying start distance* (FD) into the model definition as an additional parameter. Incorporating FD parameter to Equation 6 yields Equation 9.

$$
\begin{aligned}
t(d) \quad &= \left(TAU \times W\left(-e^{\frac{-d+FD}{MSS \times TAU}} - 1\right) + \frac{d+FD}{MSS} + TAU\right) \\
&\quad - \left(TAU \times W\left(-e^{\frac{FD}{MSS \times TAU}} - 1\right) + \frac{FD}{MSS} + TAU\right)
\end{aligned}
\tag{9}
$$

Similar to the *Fixed TC* and *Estimated TC* models, the FD parameter has the option to either be estimated or fixed. If the flying start distance is a known value (e.g., 0.5 m), it can be utilized as a constant parameter. Models that utilize fixed TC parameter value are denoted as *Fixed flying star distance* (*Fixed FD*) models. On the other hand, the model in which the FD parameter is estimated together with MSS and TAU parameters is denoted as the *Estimated flying star distance* (*Estimated FD*) model.

Table 3 encompasses the complete set of model estimates for a trio of siblings, comprising both the *Fixed 0.5m FD* and *Estimated FD* models. A visual depiction in the form of Figure 8 accompanies Table 3. In order to standardize the comparison of estimates, the *absolute percent difference* from the *true* parameter value is employed. A visual anchor is employed in the form of a fixed 5% absolute percent difference, represented by a dotted horizontal line in Figure 8, to facilitate visual comparison among the models.

The *No Correction* model generated parameters that were biased toward Ben and Cole. The *Fixed +0.3s TC* model produced unbiased parameters for Ben, but resulted in a greater degree of parameter bias for Andrew and Cole. The introduction of a fixed time correction of 0.5 seconds in the *Fixed +0.3s TC* model has resulted in a significant bias for all three siblings. The *Estimated TC* and *Estimated FD* models exhibited minimal bias for Andrew, whereas they effectively rectified the model parameters for Ben and Cole. The estimation of the parameters using the *Estimated FD* model for Cole, a brother who starts at gunfire and has additional reaction time involved in his split times, was unsuccessful. The reason for this is that the *Estimated FD* model is *ill-defined* in that particular case and is incapable of producing a negative flying distance. The model parameters for Ben were successfully adjusted to eliminate bias using the *Fixed 0.5m FD* model. However, this result in a significant bias for Andrew and Cole. In general, the parameter that exhibited the least amount of bias was MSS. This suggests that, in the context of this uncomplicated simulation, MSS is the most resilient parameter among the four.

It is important to acknowledge that every model definition incorporates a specific assumption regarding the mechanism of data generation (i.e., *data-generating process*, or DGP). The *No Correction* model postulates the ideal alignment of sprint initiation with the commencement of timing. The *Estimated TC* model incorporates a basic intercept that can facilitate the estimation of parameters in situations where a time shift is presumed to be present and constant, such as when reaction time is a factor or when the initial timing gate is triggered prematurely. The utilization of the *Estimated TC* model is also applicable in scenarios where "flying start" is employed. However, it presupposes a constant time shift, which is not the case in such situations due to the velocity already acquired at the start. The *Fixed FD* and *Estimated FD* models presuppose the presence of a flying sprint in the data-generating process. As evidenced by the estimates presented in Table 3, these models may be ill-defined in cases where there is no flying distance component, but a temporal displacement is present. Each of the three models postulates that athletes undergo acceleration in accordance with Equation 1. As demonstrated in Figure 5, this is not necessarily the case.

The *No Correction* model is a widely utilized approach for estimating short sprint parameters, whereas the *Estimated TC* and *Estimated FD* models are novel model definitions that require additional scientific validation for their application.

Table 3. *Estimated sprint parameters for Andrew, Ben, and Cole using (1) No Correction, (2) Fixed +0.3s time correction (Fixed +0.3s TC), (3) Fixed +0.5s time correction (Fixed +0.5s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models. Numbers in the brackets indicate the absolute percent difference from the true parameter value. For easier visual comprehension, absolute percent differences are depicted separately in Figure 8.* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1}); TC - time correction; FD - flying distance*

Model	**Athlete**	**MSS**	**TAU**	**MAC**	**PMAX**	**TC**	**FD**
	True	*9.50*	*1.36*	*7.00*	*16.62*		
	Andrew (theoretical)	9.54 (0.4%)	1.37 (1.0%)	6.96 (0.6%)	16.6 (0.2%)		
No correction	Ben (flying start)	8.90 (6.3%)	0.73 (46.0%)	12.15 (73.5%)	27.02 (62.5%)		
	Cole (gunfire)	10.36 (9.0%)	1.96 (44.8%)	5.27 (24.7%)	13.66 (17.9%)		
	Andrew (theoretical)	10.97 (15.5%)	2.37 (74.3%)	4.64 (33.7%)	12.72 (23.5%)		
Fixed +0.3s TC	Ben (flying start)	9.51 (0.1%)	1.31 (3.2%)	7.24 (3.5%)	17.22 (3.6%)		
	Cole (gunfire)	12.92 (36%)	3.55 (161.4%)	3.64 (48%)	11.76 (29.2%)		
	Andrew (theoretical)	12.92 (36.0%)	3.55 (161.4%)	3.64 (48.0%)	11.76 (29.2%)		
Fixed +0.5s TC	Ben (flying start)	10.29 (8.3%)	1.88 (38.8%)	5.46 (22.0%)	14.05 (15.5%)		
	Cole (gunfire)	16.99 (78.8%)	5.85 (331.1%)	2.90 (58.5%)	12.33 (25.8%)		
	Andrew (theoretical)	9.56 (0.6%)	1.38 (2.0%)	6.90 (1.4%)	16.50 (0.8%)	0.01	
Estimated TC	Ben (flying start)	9.50 (0.0%)	1.30 (4.1%)	7.30 (4.3%)	17.33 (4.2%)	0.30	
	Cole (gunfire)	9.56 (0.6%)	1.38 (2.0%)	6.90 (1.4%)	16.50 (0.8%)	-0.19	
	Andrew (theoretical)	11.75 (23.7%)	2.96 (118.2%)	3.97 (43.3%)	11.66 (29.8%)		0.50
Fixed 0.5m FD	Ben (flying start)	9.52 (0.2%)	1.36 (0.5%)	6.98 (0.3%)	16.61 (0.1%)		0.50
	Cole (gunfire)	15.83 (66.7%)	5.41 (299%)	2.92 (58.2%)	11.58 (30.4%)		0.50
	Andrew (theoretical)	9.56 (0.6%)	1.38 (2.0%)	6.90 (1.4%)	16.50 (0.8%)		0.00
Estimated FD	Ben (flying start)	9.56 (0.6%)	1.40 (3.1%)	6.83 (2.4%)	16.31 (1.9%)		0.54
	Cole (gunfire)						

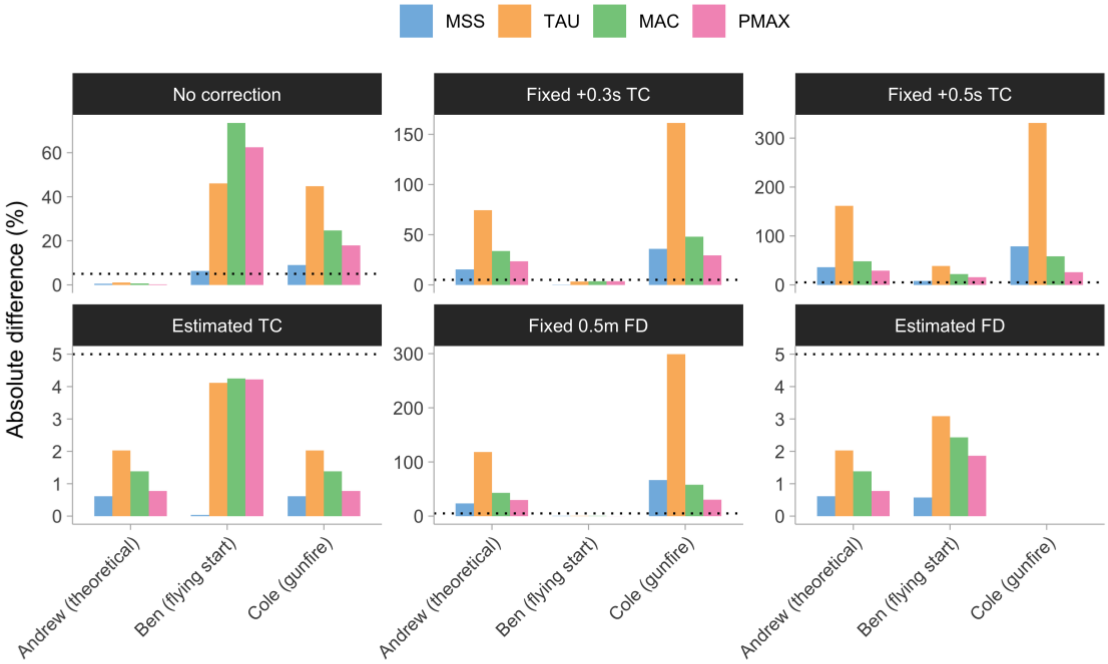


Figure 8. *Estimated sprint parameters for Andrew, Ben, and Cole using (1) No Correction, (2) Fixed +0.3s time correction (Fixed +0.3s TC), (3) Fixed +0.5s time correction (Fixed +0.5s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models expressed as absolute percent difference from the true parameter value. Dotted horizontal lines represent a 5% absolute difference used as a visual anchor.* ***Note.*** *MSS – maximum sprinting speed (expressed in* ms^{-1}*); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in* ms^{-2}*); PMAX – maximal relative power (expressed in* $W kg^{-1}$*); dotted horizontal line - visual anchor using fixed 5% absolute percent difference, used for easier visual comparison between models.*

2 PROBLEM, SCOPE, AND AIM OF THE STUDY

The effect of starting position on the short sprint modeling using timing gates represents a practical problem for practitioners and researchers. Elimination of the bias in estimated parameters introduced due to the flying start is imperative to enhance the validity of short sprint profiles and to improve their sensitivity to intervention changes. The current study aims to examine the aforementioned bias and investigate the impact of various mono-exponential models on the validity and sensitivity of brief sprint profiling.

The scope of the study was exploration, evaluation, and validation of the *No Correction*, *Fixed TC*, *Estimated TC*, *Fixed FD*, and *Estimated FD* mono-exponential models for estimating short sprints parameters (i.e., MSS, TAU, MAC, and $PMAX$) using timing gates under different flying start conditions. The aim of this study was to explore the behavior of these models and to evaluate their ability to estimate short sprint parameters, as well as to estimate their sensitivity to short sprint parameter changes due to the training interventions.

The proposed models were subjected to exploration, evaluation, and validation through two methods: (1) simulation and (2) athlete-based validation against the criterion measurement (i.e., the laser gun). These two methods were employed in two distinctive, yet complementary, parts of this study.

2.1 Specific aims of the first part of the study

The objective of the first part of the study was to investigate the behavior of *No Correction*, *Estimated TC*, and *Estimated FD* mono-exponential models under simulated and known conditions. This was necessary to provide a theoretical comprehension of the short sprints modeling's limitations and expected errors.

In addition to estimating the *agreement* between *true* and *estimated* parameter values (i.e., precision), practitioners are frequently interested in whether estimated measures can be used to trace changes in *true* measures. Consequently, the second objective of the first part of the study was to assess the sensitivity of the models to detect changes in simulated scenarios.

2.2 Specific aims of the second part of the study

The second part of the study aimed to validate the models against the *criterion* measure (i.e., the laser gun) involving athletes. In the first part of the study (i.e., simulation study), the precision and sensitivity to change of the models were evaluated against the *true* (i.e., simulated) values across different flying start distances. In the second part of the study, the precision and sensitivity to change were evaluated against the *criterion* measure, serving as the proxy to the *true* measure.

3 THE HYPOTHESIS OF THE STUDY

The following hypotheses were used for this study:

1. When estimated using the *No Correction* model using timing gates, flying start induces bias in short sprint parameters,
2. *Estimated TC* and *Estimated FD* models alleviate this bias and improve the sensitivity of short sprint profiling to detect true change in individual sprint characteristics.

4 POTENTIAL BENEFITS OF THE STUDY

Sprint profiling is utilized in sports with three aims: (1) to compare individuals and groups, (2) to estimate training intervention effects on both individuals and groups, and (3) to use profiles to individualize training (Morin & Samozino, 2016). Improving the precision and sensitivity of the profiles will benefit practitioners when pursuing those tasks by increasing confidence in differences, changes, and decisions, respectively.

If proven to alleviate bias associated with flying sprint during timing gates measurement and improve profiling sensitivity, then *Estimated TC* and *Estimated FD* models might replace the *No Correction* model with practitioners and become standardized estimation models.

5 THE FIRST PART OF THE STUDY

The primary objective of this part of the study is to investigate the behavior of the *No Correction*, *Estimated TC*, and *Estimated FD* mono-exponential models under both simulated and known settings. The inclusion of this component within the study was necessary in order to establish a theoretical comprehension of the constraints and anticipated inaccuracies associated with the modeling of short sprints. This theoretical foundation then guided the implementation of a more pragmatic second part of the study, which involved athletes.

5.1 Methods

5.1.1 Simulation design

In this part of the study, timing gate split times were generated using *true* short sprint parameters: (1) MSS (ranging from 7 to 11 ms^{-1}, in increments of 0.05 ms^{-1}, resulting in a total of 81 unique values), (2) MAC (ranging from 7 to 11 ms^{-2}, in increments of 0.05 ms^{-2}, resulting in a total of 81 unique values), and (3) flying distance (FD) (ranging from 0 to 0.5 m, in increments of 0.01 m, resulting in a total of 51 unique values). Each flying sprint distance consists of 6,561 MSS and MAC combinations.

Split times were generated assuming timing gates positioned at 5, 10, 20, 30, and 40 meters, with the rounding to the closest 10 ms. In total, there were 334,611 sprints simulated.

5.1.2 Statistical analyses

For each stimulated sprint, MSS, MAC, TAU, and $PMAX$ were estimated using the (1) *No Correction*, (2) *Estimated TC*, and (3) *Estimated FD models*. *Percent difference* ($\%Diff$) (Equation 10) estimator was used to evaluate the agreement between *true* and estimated parameter values.

$$\%Diff = 100 \times \frac{estimated - true}{true} \qquad (10)$$

$Median$ and 95% *highest-density continuous interval* ($HDCI$) (Kruschke, 2015, 2018; Kruschke & Liddell, 2018a, 2018b; Makowski et al., 2019) were used to summarize the $\%Diff$ distribution across simulated sprints.

Region of practical equivalence ($ROPE$), as well as the proportion of the simulations that lie within $ROPE$ (*inside* $ROPE$; expressed as a percentage) (Jovanović, 2020a; Kruschke, 2015, 2018; Kruschke & Liddell, 2018a, 2018b; Makowski et al., 2019) were calculated to provide a magnitude interpretation of the $\%Diff$ distribution. For the purpose of this part of the study, $ROPE$ was assumed to be equal to 95% $HDCI$ of the $\%Diff$ using the *No Correction* model and no flying distance. This value denotes the minimum level of inaccuracy, indicating the highest level of agreement that may be attained. The determination is only based on the precision of the timing gates measurement (i.e., rounding to the closest 10 ms) as well as the parameters used in the simulation.

Practitioners are frequently concerned about whether they may utilize estimated parameter values to monitor changes in the *true* parameters in addition to estimating agreement between them. Thus, an estimate of the *sensitivity* represents a piece of crucial information to decide whether a given measure can be practically used to monitor changes. A *minimal* *detectable change* estimator with 95% confidence ($\%MDC_{95}$) (Furlan & Sterr, 2018; Jovanović, 2020a) was utilized to estimate this sensitivity. The $\%MDC_{95}$ value might be regarded as the minimum amount of change that needs to be observed in the estimated parameter for it to be considered a *true* change.

Percent residual standard error ($\%RSE$) of the linear regression between *true* (predictor) and estimated parameter values (outcome) (Equation 11) was utilized to calculate $\%MDC_{95}$ (Equation 12). Since simulated data with the known *true* values were utilized, $\%RSE$ represents the *percent standard error of the measurement* ($\%SEM$) in the estimated parameters.

$$\%RSE = \sqrt{\frac{\sum_{i=1}^{N}\left(100 \times \frac{y_i - \widehat{y}_i}{\widehat{y}_i}\right)^2}{N-2}} \qquad (11)$$

$$\%MDC_{95} = \%RSE \times \sqrt{2} \times 1.96 \qquad (12)$$

In addition to providing $\%MDC_{95}$ for the estimated parameters, the lowest $\%MDC_{95}$ was estimated using the *No Correction* model and no flying distance ($\%MDC_{95}^{lowest}$). Theoretically, $\%MDC_{95}^{lowest}$ represents the lowest $\%MDC_{95}$ that can be achieved, and it is limited purely by the timing gates measurement precision (i.e., rounding to the closest 10 ms) and simulated parameters. $\%MDC_{95}^{lowest}$ is used only as a reference to evaluate estimated parameters' $\%MDC_{95}$.

The analyses were conducted on split times that were pooled together, meaning that all flying distances were taken into account. Additionally, the analyses were also done across each individual flying distance. The hypothesis posited that the *Estimated FD* model would yield the greatest estimates for $inside\ ROPE$ and the lowest estimates for $\%MDC_{95}$.

The open-source **shorts** package (Jovanović, 2023; Jovanović & Vescovi, 2022) created in R 4.2.1 language (R Core Team, 2022) was used, together with RStudio (version 2023.06.1+524), to perform statistical analyses and graph construction.

5.2 Results

5.2.1 Model fitting

The *Estimated FD* model failed to be fitted for certain parameter combinations in the simulated data, which can be found in Table 4. The probable cause for the unsuccessful model fittings is the amalgamation of a very small flying distance and the precision of the timing gates' measurements, resulting in *Estimated FD* being an ill-defined model that cannot be fitted. These sprints were disregarded from further analysis.

***Table 4**. Failures in the estimation of the Estimated flying start distance (Estimated FD) model*

Flying distance (m)	Not fitted	Total	Not fitted (%)
0.00	1765	6561	26.90
0.01	12	6561	0.18
0.02	16	6561	0.24
0.03	10	6561	0.15
0.04	4	6561	0.06
0.05	1	6561	0.02

5.2.2 Percent difference

5.2.2.1 Region of practical equivalence

The estimated Region of Practical Equivalence (ROPE) values for MSS, MAC, TAU, and $PMAX$ are equal to -0.30 to 0.33%, -0.73 to 0.74%, -1.03 to 1.00%, and -0.50 to 0.50%, respectively, as presented in Table 5. These values are also visually represented by the grey horizontal bars in Figure 9 and Figure 10. A noteworthy discovery indicates that when considering simulation parameters, specifically the accuracy of timing gates to the nearest 10 ms, MSS exhibits the smallest $ROPE$ in comparison to other short sprint parameters. Given the theoretical simulation, it can be inferred that the parameter with the highest degree of precision in estimation is the MSS, as it is represented by the lowest estimation error denoted by $ROPE$. On the contrary, the estimations of TAU and MAC exhibit the lowest degree of precision.

5.2.2.2 Pooled analysis

The analysis was conducted by pooling all flying distances together. The pooled analysis serves as a comprehensive evaluation of the concordance between the actual (i.e., *true*) and estimated parameter values under various simulated scenarios.

The distribution of the pooled percent difference ($\%Diff$) is illustrated in Figure 9. As anticipated, the *Estimated FD* model exhibited the greatest *inside* $ROPE$ parameter values (from 20 to 72%), with the narrowest 95% $HDCI$s (from -5 to 5%) and was devoid of any bias.

Conversely, the *No Correction* model exhibited suboptimal performance, as evidenced by its lowest values for the *inside* $ROPE$ parameter (from 2 to 2%), the widest 95% $HDCI$s (from -46 to 80%), and the apparent bias indicated by the *median* parameter values falling outside of $ROPE$ (from -35 to 49%). Furthermore, upon conducting a visual examination of Figure 9, it was observed that the estimated $\%Diff$ parameter values exhibit a *non-normal distribution*, thereby necessitating additional analysis across varying flying distance values.

The *Estimated TC* model exhibited comparable performance to the *Estimated FD* model, albeit with a slightly lower value for the *inside* $ROPE$ parameter (from 9 to 67%). Additionally, the *Estimated TC* model displayed wider 95% $HDCI$s, and demonstrated a discernible bias, albeit significantly smaller than the bias observed in the *No Correction* model (from -3 to 3%).

The summary of the pooled analysis results for each model and short sprint parameter can be found in Table 5.

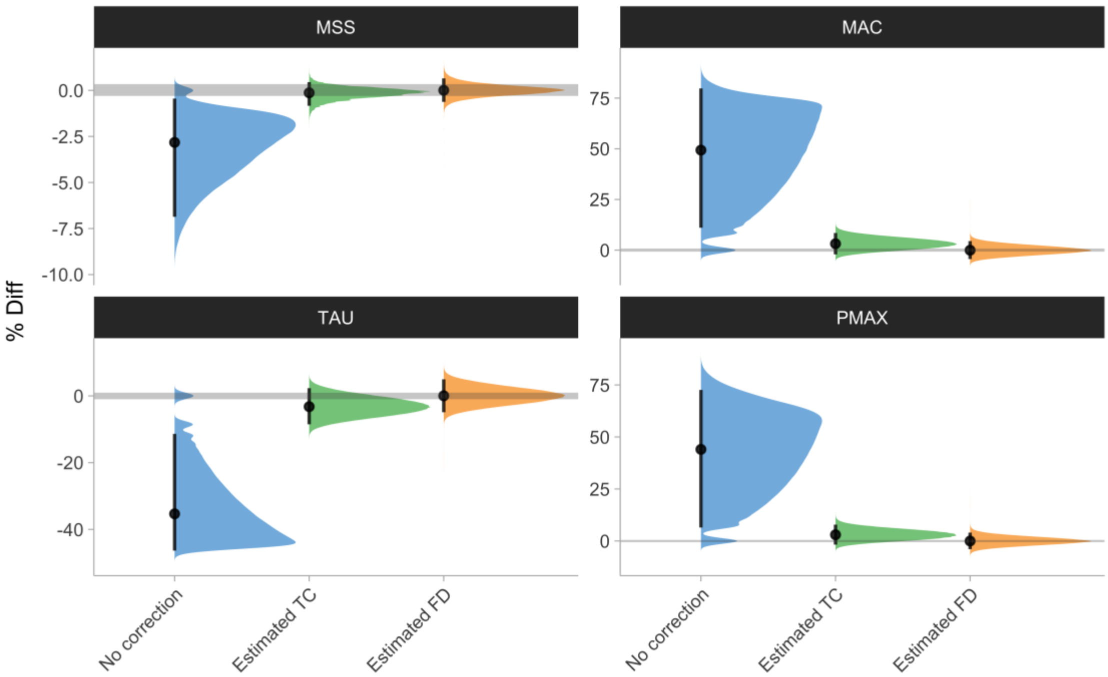


Figure 9. *Pooled distribution of the percent difference (*$\%Diff$*) for (1) No Correction (blue), (2) Estimated time correction (Estimated TC) (green), and (3) Estimated flying start distance (Estimated FD) (orange) models. Error bars represent the distribution median and 95% highest-density continuous interval (95%* $HDCI$*). A grey area represents the parameter region of practical equivalence (ROPE) (assumed to be equal to 95%* $HDCI$ *of the* $\%Diff$ *using the No Correction model and no flying distance).* ***Note.*** *MSS – maximum sprinting speed (expressed in* ms^{-1}*); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in* ms^{-2}*); PMAX – maximal relative power (expressed in* Wkg^{-1}*)*

Table 5. *Region of practical equivalence ($ROPE$), a summary of percent difference ($\%Diff$) distribution, and percentage of the simulations that lie within the region of practical equivalence ($inside$; $ROPE$) estimated using pooled simulation dataset for (1) No Correction, (2) Estimated time correction (Estimated TC), and (3) Estimated flying start distance (Estimated FD) models.* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1}); HDCI – highest-density continuous interval*

Parameter	ROPE (%)	Model	% Diff	Inside ROPE (%)
MSS	-0.30 to 0.33%	No correction	median -3%, 95% HDCI [-7 to 0%]	2%
		Estimated TC	median 0%, 95% HDCI [-1 to 0%]	67%
		Estimated FD	median 0%, 95% HDCI [-1 to 1%]	72%
MAC	-0.73 to 0.74%	No correction	median 49%, 95% HDCI [11 to 80%]	2%
		Estimated TC	median 3%, 95% HDCI [-2 to 8%]	12%
		Estimated FD	median 0%, 95% HDCI [-4 to 4%]	25%
TAU	-1.03 to 1.00%	No correction	median -35%, 95% HDCI [-46 to -11%]	2%
		Estimated TC	median -3%, 95% HDCI [-9 to 2%]	16%
		Estimated FD	median 0%, 95% HDCI [-5 to 5%]	31%
PMAX	-0.50 to 0.50%	No correction	median 44%, 95% HDCI [6 to 73%]	2%
		Estimated TC	median 3%, 95% HDCI [-2 to 8%]	9%
		Estimated FD	median 0%, 95% HDCI [-4 to 4%]	20%

5.2.2.3 Analysis across flying distances

The analysis results for each flying distance in the simulation are depicted in Figure 10. Computed $inside\ ROPE$ estimates are illustrated in Figure 11.

As anticipated, the *No Correction* model exhibited a growing bias as the flying distance increased (from -46 to 76%). This was evidenced by the broadest 95% $HDCI$s (from -47 to 84%) and the most minimal estimated parameter values that were within the Region of Practical Equivalence (from 0 to 95%).

The analysis revealed that the *Estimated TC* model exhibited a small bias trend across flying distances (from -6 to 6%), resulting in decreasing $inside\ ROPE$ performance (from 0 to 75%; see Figure 11). However, it is noteworthy that the model's 95% $HDCI$s (from -10 to 11%) were much smaller than those of the *No Correction* model.

The *Estimated FD* model exhibited no bias and demonstrated consistent $inside\ ROPE$ across various flying distances. The graphical representation of this observation can be found in Figure 11. Additionally, the *Estimated FD* displayed narrow 95% $HDCI$s (from -5 to 6%).

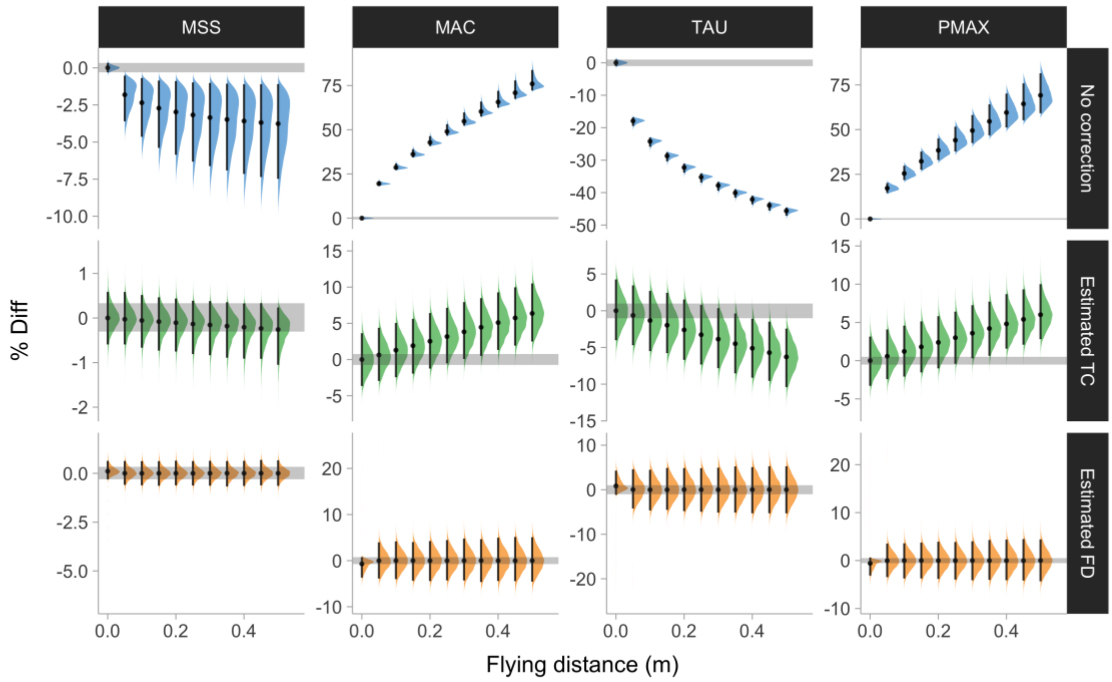


Figure 10. *Distribution of the percent difference (%$Diff$) across every flying distance in the simulation for (1) No Correction (blue), (2) Estimated time correction (Estimated TC) (green), and (3) Estimated flying start distance (Estimated FD) (orange) models. Error bars represent the distribution median and 95% highest-density continuous interval (95% $HDCI$). A grey area represents the parameter region of practical equivalence ($ROPE$) (assumed to be equal to 95% $HDCI$ of the %$Diff$ using the No Correction model and no flying distance). For the less crowded visualization, flying distance in increments of 0.05 m is plotted.* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

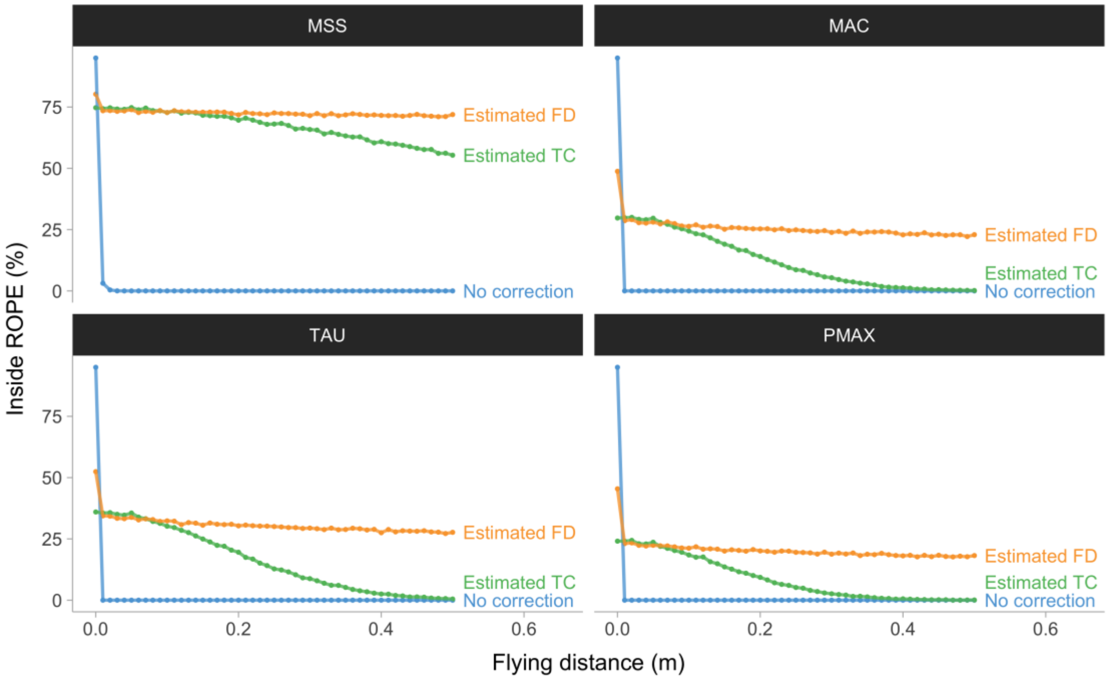


Figure 11**. Percentage of the simulations that lie within the region of practical equivalence (inside ROPE) estimated across every flying distance in the simulation for (1) No Correction (blue), (2) Estimated time correction (Estimated TC) (green), and (3) Estimated flying start distance (Estimated FD) (orange) models.* ***Note. *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

5.2.3 Minimal detectable change

5.2.3.1 Lowest Minimum Detectable Change

The estimated lowest minimum detectable change ($\%MDCs_{95}^{lowest}$) is presented in Table 6 and visualized as dashed grey horizontal lines in Figure 12. The values for MSS, MAC, TAU, and $PMAX$ are 0.45%, 1.06%, 1.47%, and 0.70%, respectively. The dashed grey horizontal lines in Figure 12 indicate these values. A noteworthy discovery indicates that, given simulation parameters (particularly the precision of the timing gates to the closest 10 ms), MSS exhibits the least $\%MDCs_{95}^{lowest}$ in comparison to other short sprint parameters. In contrast, the estimations of TAU and MAC changes exhibit the least precision.

5.2.3.2 Pooled analysis

The pooled minimum detectable changes ($\%MDCs_{95}$) signifies a projection of the sensitivity to identify authentic alterations with a confidence level of 95% when the flying start distance is not standardized. This projection is made within the simulation parameter limits, which range from 0 to 0.5 meters distance of the flying start. As anticipated, the *No Correction* model exhibited the greatest $\%MDCs_{95}$ (from 3 to 44%). Conversely, *Estimated TC* and *Estimated FD* models demonstrated notably smaller $\%MDCs_{95}$, with values of from 1 to 8% and from 1 to 7%, respectively (refer to Table 6).

A noteworthy observation is that the MSS parameter exhibited considerably low $\%MDCs_{95}$ across all models (from 1 to 3%), including the *No Correction* model. The findings suggest that the *No Correction* model can be utilized to monitor modifications in MSS, even in cases where short sprints are employed without standardized flying distance, based on simulation parameters. In contrast, the TAU, MAC, and $PMAX$ parameters require a significantly greater amount of change that needs to be observed for them to be considered a *true* change. The respective values for the $\%MDCs_{95}$ are from 7 to 44%, from 6 to 37%, and from 6 to 36%.

Table 6. *Minimal detectable change using 95% confidence level ($\%MDCs_{95}$) estimated using pooled simulation dataset for (1) No Correction, (2) Estimated time correction (Estimated TC), and (3) Estimated flying start distance (Estimated FD) models.* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

Parameter	$\%MDCs_{95}^{lowest}$	No correction	Estimated TC	Estimated FD
MSS	0.45 %	3 %	1 %	1 %
MAC	1.06 %	37 %	7 %	6 %
TAU	1.47 %	44 %	8 %	7 %
PMAX	0.70 %	36 %	7 %	6 %

5.2.3.3 Analysis across flying distances

The analysis of $\%MDCs_{95}$ across various flying distances reveals intriguing and unexpected trends, as depicted in Figure 12. In relation to each short sprint parameter, the *Estimated TC* model exhibited consistent and reduced values of minimum detectable change ($\%MDCs_{95}$) in comparison to the *Estimated FD* (from 1 to 6% and from 1 to 8%, respectively). These results are unexpected because, in contrast to *Estimated FD*, *Estimated TC* may be more sensitive in detecting changes given the simulation parameters, despite showing bias in approximating short sprint parameters (please refer to the results section on Percent difference, particularly Figure 11).

An additional noteworthy discovery is that the *No Correction* model, despite displaying a significant inclination towards biased estimations of short sprint parameters (please refer to the results section on Percent difference, particularly Figure 10), exhibited the least $\%MDCs_{95}$ for the MAC and TAU parameters (from 1 to 5% and from 1 to 3%, respectively). The aforementioned observation suggests that by standardizing short sprint measurement, wherein athletes execute the activity at an identical flying start distance, and considering the simulation parameters, the *No Correction* model may exhibit the highest level of sensitivity in identifying changes in MAC and TAU parameters. Unfortunately, this is not the case for MSS and $PMAX$ parameters (from 0 to 3% and from 1 to 9%, respectively).

In the context of assessing changes in short sprint parameters, the parameter that exhibits the highest degree of sensitivity for detection is the MSS, as indicated by $\%MDCs_{95}$ values ranging from 0 to 3%, in comparison to MAC (from 1 to 7%), TAU (from 1 to 8%), and $PMAX$ (from 1 to 9%).

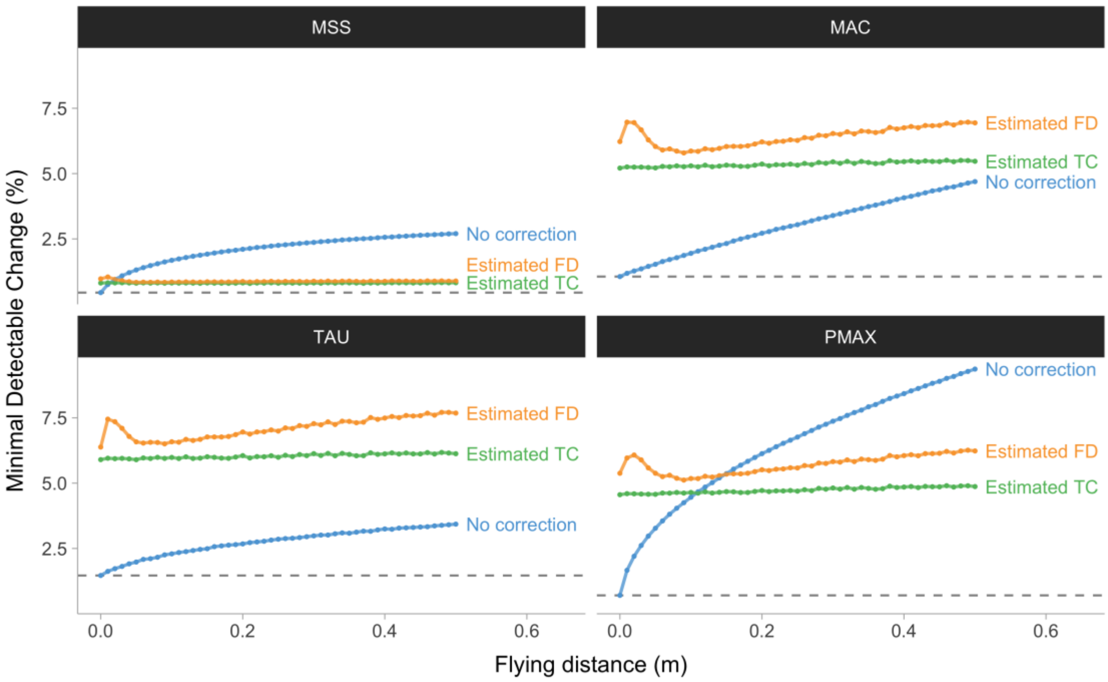


Figure 12. *Estimated minimal detectable change using 95% confidence level ($\%MDCs_{95}$) across every flying distance in the simulation for (1) No Correction, (2) Estimated time correction (Estimated TC), and (3) Estimated flying start distance (Estimated FD) models. The dashed line represents the lowest $\%MDCs_{95}$ estimated using the No Correction model and no flying distance ($\%MDCs_{95}^{lowest}$).* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

5.3 Discussion

The simulation utilized in the first part of the study exhibited both anticipated and unanticipated theoretical discoveries. The anticipated results include three main outcomes. First, the *No Correction* model was expected to exhibit bias and low performance in estimating short sprint parameters, particularly in relation to the *inside ROPE* metric. Second, the *Estimated TC* model was predicted to demonstrate less bias and a higher level of performance within the *inside ROPE* metric. Lastly, the *Estimated FD* model was expected to exhibit no bias and the highest level of performance within the *inside ROPE* metric. These three outcomes were all confirmed with the results of the simulation analysis.

The first part of the study yielded an unforeseen outcome, namely, the superior performance of the *No Correction* model in accurately estimating the change sensitivity of the MAC and TAU parameters, surpassing the performance of the other two models.

When making estimations of short sprint parameters across models based on simulation parameters, it is observed that the MSS parameter and its change can be estimated with greater precision in comparison to the parameters of TAU, MAC, and $PMAX$, as well as their respective changes.

This part of the study presented the $ROPE$s and $\%MDCs_{95}^{lowest}$, in addition to evaluating model performances. These findings have the potential to contribute to the advancement of validity and reliability studies that assess the performance of short sprint models among actual athletes, utilizing timing gates that are positioned at precise distances and with exact rounding utilized in the simulation.

The key point for practitioners is that in addition to standardizing the sprint starting technique for short sprint performance monitoring, it would be prudent to employ and monitor the outcomes of all three models. The *Estimated FD* model is capable of providing unbiased estimations of present performance, whereas the *No Correction* model may exhibit greater sensitivity in identifying changes in TAU and MAC parameters.

It is advisable to exercise prudence when considering this pragmatic inference, as it is founded upon the outcomes of this theoretical simulation. Further research is required to assess the efficacy of these three models by utilizing actual athletes, as demonstrated in the second part of the study.

6 THE SECOND PART OF THE STUDY

Second part of the study involves the assessment of athletes' sprinting performance over a distance of 30 meters, commencing from a stationary position. The measurement of their performance was conducted through the use of a laser gun and timing gates. Since the *true* individual parameters are unknown, laser gun estimates served as the *criterion* measure, used to compare and evaluate timing gates estimates. In addition to estimating the agreement of the timing gates and laser gun, the sensitivity of the measures to detect changes in parameters was also established.

6.1 Methods

6.1.1 Participants

This part of the study involved the participation of 31 basketball players, comprising of 23 males (age of 16.1 ± 1.0 years, height of 188.3 ± 7.5 cm, and body mass of 69.5 ± 10.8 kg) and 8 females (age of 16.1 ± 1.4 years, height of 170.5 ± 7.5 cm, and body mass of 60.9 ± 7.6 kg). These players were selected from the highest youth level of Hungary. The participants were duly apprised of the potential hazards and advantages of their involvement in the study, and a written authorization was procured from both the participants and their parents. The research adhered to the ethical guidelines approved by the Faculty of Sport and Physical Education at the University of Belgrade, Serbia (02-877/23-2, 9th May, 2023), and was conducted in accordance with the most recent version of the Declaration of Helsinki.

6.1.2 Procedure

Prior to evaluating sprint performance, a standardized warm-up protocol lasting 15 minutes was executed. The warm-up involved a series of mobility and running exercises performed repeatedly within a 20-meter distance, culminating in three incremental sub-maximal sprints covering a distance of 30 meters. Following the warm-up, the participants executed two trials of maximal sprints covering a distance of 30 m, with a minimum rest period of 3 minutes between each trial. If equipment failure occurred, an additional sprint was executed as necessary. The sprint times were recorded using a set of five wireless photocell pairs (WittyGATE™ v1.5.34, Microgate S.r.l, Bolzano, Italy) positioned at the start line, as well as at distances of 5, 10, 20, and 30 m (Figure 13). The accuracy of the timing measurements was 0.01 s. At the beginning of each sprint, the participants assumed a split stance with their lead foot positioned behind a line affixed to the floor at a distance of 0.5 m from the initial pair of photocells. The photocells were situated at a height of 1 m to prevent premature interruption of the beam by the upper body during the starting position. The velocity measurements were continuously recorded for each attempt utilizing a laser gun (CMP3 Distance Sensor, Noptel Oy, Oulu, Finland) at a sampling rate of 2.56 KHz. A polynomial function was utilized to model the relationship between distance and time, which was subsequently resampled at a frequency of 1,000 Hz through the use of Musclelab™ v10.232.107.5298 (Ergotest Technology AS, Langesund, Norway). The laser gun was situated at a distance of roughly 3 m from the initial timing gate, while the reference point (i.e., zero distance) was established at a distance of 1 m behind the initial timing gate (Figure 13). The entirety of the sprints were executed within the confines of an indoor basketball facility.

Figure 13. *Laser gun and timing gates setup.*

To compare the short sprint mechanical parameters: (1) the maximal sprinting speed (MSS), (2) the relative acceleration (TAU), (3) the maximal acceleration (MAC), and (4) the net relative propulsive power ($PMAX$) were calculated based upon the sprint times at 5, 10, 20, and 30 m measured with the timing gates and with the laser system by using open-source **{shorts}** package (Jovanović, 2023; Jovanović & Vescovi, 2022). The mechanical parameters for the timing gates were estimated through five different models: (1) *No Correction*, (2) Fixed +0.3 s time correction (*Fixed +0.3s TC*), (3) Estimated time correction (*Estimated TC*), (4) Fixed 0.5 m flying start distance (*Fixed 0.5m FD*), and (5) Estimated flying start distance (*Estimated FD*) models explained previously. Sprint mechanical parameters for the laser gun were estimated using the *raw* velocity-time signal and time correction polynomial model (Equation 5), after filtering out velocities below 0.5 ms^{-1} using *smoothed* velocity provided by the Musclelab™ software.

The inclusion criteria for the sprint trials encompassed both timing gates and laser gun data. The study excluded trials that exhibited deceleration in timing gate split times, wherein the mean velocity of a particular split was slower than that of the preceding split. Furthermore, laser gun trials that exhibited a trace length of less than 29 meters were excluded from subsequent analysis.

6.1.3 Statistical analyses

6.1.3.1 Descriptive analysis

Simple descriptive analysis was performed on (1) trial split times and average split velocities, (2) trial short sprint parameters estimated using laser gun and timing gates, (3) pooled (i.e., Trial 1 and Trial 2) relationship between first and last average split velocity using timing gates, (4) pooled relationship between MSS estimates and 20-30 m average split velocity, and (5) pooled relationship between MAC estimates and 0-5 m average split velocity.

For descriptive analyses (1-2), in addition to providing descriptive summary using $median$ and 25th and 75th quantiles (i.e., interquartile range) for the split times, average split velocities, and estimated short sprint parameters, *percent difference between trials* ($\%Diff$; Equation 13) and *percent coefficient of variation* ($\%CV$; Equation 14) were calculated for each individual athlete and summarized using the aforementioned method.

$$\%Diff = 100 \times \frac{(Trial_2 - Trial_1)}{Trial_1} \qquad (13)$$

$$\%CV = 100 \times \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Trial_i - \overline{Trial}\right)^2}}{\overline{Trial}} \qquad (14)$$

For descriptive analyses (3-5), simple linear regression has been fitted with variance explained (R^2) and *p-value* provided. Statistical significance is set at $p < 0.05$.

6.1.3.2 Agreement between laser gun and timing gates

Agreement between short sprint parameter estimates using laser gun and timing gates were estimated using *percent difference* ($\%Diff$) estimator (Equation 15), which was calculated for every athlete and trial. These were summarized using $median$ and 25th and 75th quantiles (i.e., interquartile range; IQR).

$$\%Diff = 100 \times \frac{(Timing\ Gates - Laser)}{Laser} \qquad (15)$$

Using individual percent difference scores, *percent bias* ($\%Bias$, or mean percent difference; Equation 16) and *percent mean absolute difference* ($\%MAD$; Equation 17) were calculated.

$$\%Bias = \frac{1}{N}\sum_{i=1}^{N}(\%Diff) \qquad (16)$$

$$\%MAD = \frac{\sum_{1}^{N}\left|\%Diff_i - \overline{\%Diff}\right|}{N} \qquad (17)$$

Statistical inference for $\%Bias$ and $\%MAD$ estimators were provided using the 2,000 resamples bootstrap and 95% bias-corrected and accelerated (BCa) confidence intervals (Canty & Ripley, 2017; Davison & Hinkley, 1997; Efron & Hastie, 2016; Jovanović, 2020b).

6.1.3.3 *Minimal detectable change*

Practitioners are frequently concerned about whether they may utilize estimated parameter values to monitor changes in the *true* parameters in addition to estimating agreement between them. Thus, an estimate of the *sensitivity* represents a crucial information to decide whether a given measure can be practically used to monitor changes. A *minimal detectable change* estimator with 95% confidence ($\%MDC_{95}$) (Furlan & Sterr, 2018; Jovanović, 2020a) was utilized to estimate this sensitivity. The $\%MDC_{95}$ value might be regarded as the minimum amount of change that needs to be observed in the estimated parameter for it to be considered a *true* change.

Two methods for estimating $\%MDC_{95}$ were utilized. The first method utilizes pooled (i.e., Trial 1 and Trial 2) agreement between laser gun and timing gates, while the second method utilizes the differences between trials.

6.1.3.3.1 MDC using an agreement with Laser

The sensitivity of the timing gates to detect change in parameters, estimated using agreement with the laser gun, assumes that there is no random error in laser gun estimates. In other words, this method assumes that the laser gun estimates represent the *true* parameter value.

Percent residual standard error ($\%RSE$) of the pooled (i.e., Trial 1 and Trial 2) linear regression between laser gun (predictor) and timing gates (outcome) (Equation 18) was utilized to calculate $\%MDC_{95}$ (Equation 19) for short sprint parameters. Assuming no random error involved in laser gun estimates, $\%RSE$ represents the *percent standard error of the measurement* ($\%SEM$) in the timing gates estimates.

$$\%RSE = \sqrt{\frac{\sum_{i=1}^{N}\left(100 \times \frac{y_i - \hat{y}_i}{\hat{y}_i}\right)^2}{N-2}} \qquad (18)$$

$$\%MDC_{95} = \%RSE \times \sqrt{2} \times 1.96 \qquad (19)$$

6.1.3.3.2 MDC using Trials

Another method utilized to estimate minimum-detectable change involves using Trial 1 and Trial 2. *Percent residual standard error* ($\%RSE$) of the linear regression between Trial 1 (predictor) and Trial 2 (outcome) (Equation 18) was utilized to calculate $\%MDC_{95}$ (Equation 19) for split times and average split velocities, as well as for short sprint estimates using both laser gun and timing gates.

This method of minimum-detectable change estimation combines inherent *biological variability* between trials with random error of the measures involved.

Statistical inference for $\%MDC_{95}$ estimators were provided using the 2,000 resamples bootstrap and 95% bias-corrected and accelerated (BCa) confidence intervals (Canty & Ripley, 2017; Davison & Hinkley, 1997; Efron & Hastie, 2016; Jovanović, 2020b).

6.2 Results

6.2.1 Model fitting

The dataset in Table 7 comprises the total count of trials that were subjected to subsequent analysis following the exclusion of trials that did not satisfy the established inclusion criteria. The *Estimated FD* model could not be fitted for specific athletes in Trial 1, as denoted in Table 7.

Table 7. *Final number of athletes in each trial used in the analysis for (1) Laser, (2) No Correction, (3) Fixed +0.3s time correction (Fixed +0.3s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models.*

model	Trial 1	Trial 2	Trial 2-1
Laser	27	15	15
No correction	27	15	15
Fixed +0.3s TC	27	15	15
Estimated TC	27	15	15
Fixed 0.5m FD	27	15	15
Estimated FD	25	15	15

6.2.2 Descriptive Analysis

6.2.2.1 Timing gate split times and average split velocities

Measured timing gate split times for 5, 10, 20, and 30-meter marks ranged from 0.9 to 1.41, 1.58 to 2.26, 2.78 to 3.69, and 3.95 to 5.11 seconds, respectively. Calculated average split velocities for 0-5 m ranged from 3.55 to 5.56, for 5-10 m from 3.55 to 5.56, for 10-20 m from 3.55 to 5.56, and for 20-30 m from 3.55 to 5.56 ms^{-1}. These observations are illustrated in Figure 14 and summarized using $median$ and 25th and 75th quantiles for every trial.

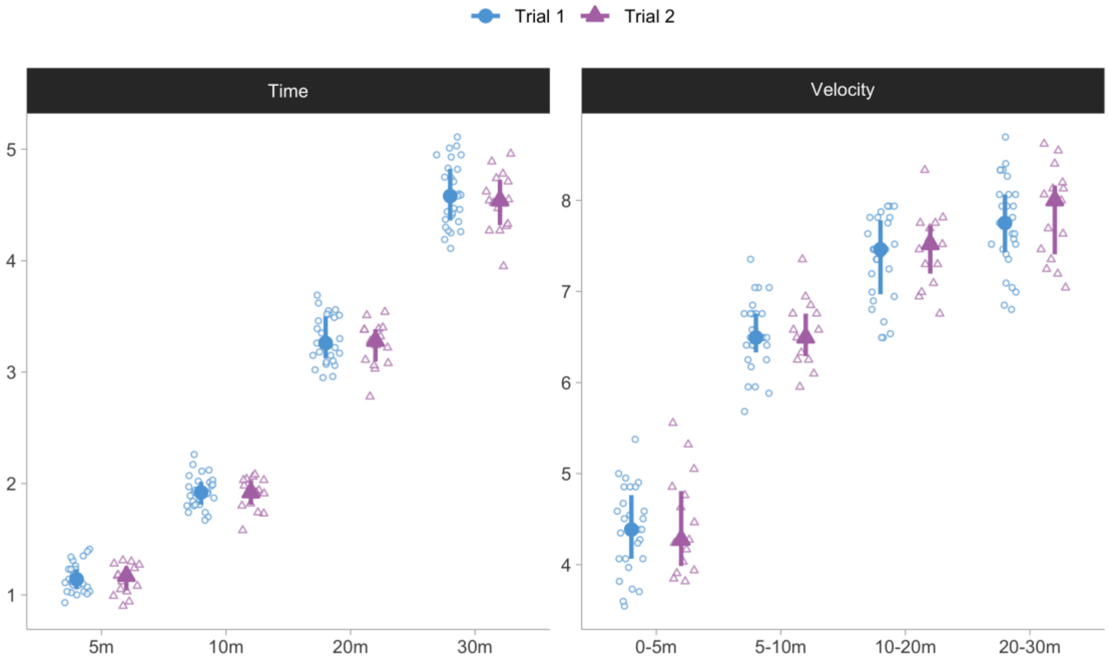


Figure 14. *Timing gate split times (expressed in s; left panel) and average split velocities (expressed in ms^{-1}; right panel) for Trial 1 (blue ●) and Trial 2 (purple ▲). Error bars represent median and 25th and 75th quantiles (i.e., interquartile range).*

Calculated individual percent differences ($\%Diff$) between Trial 1 and Trial 2 for 5, 10, 20, and 30-meter marks ranged from -11.76 to 20.00%, -7.06 to 10.30%, -6.08 to 7.30%, and -4.42 to 4.90% respectively, while for the average split velocities ranged from -16.67 to 13.30%, -7.79 to 10.00%, -3.55 to 5.00%, -4.00 to 11.2% for 0-5, 5-10, 10-20, and 20-30 m respectively (Figure 15). Visual inspection of Figure 15 indicates that the 20 and 30-meter split times, as well as the average velocity for the 10-20 and 20-30-meter splits, demonstrated the lowest spread of the individual $\%Diff$ values.

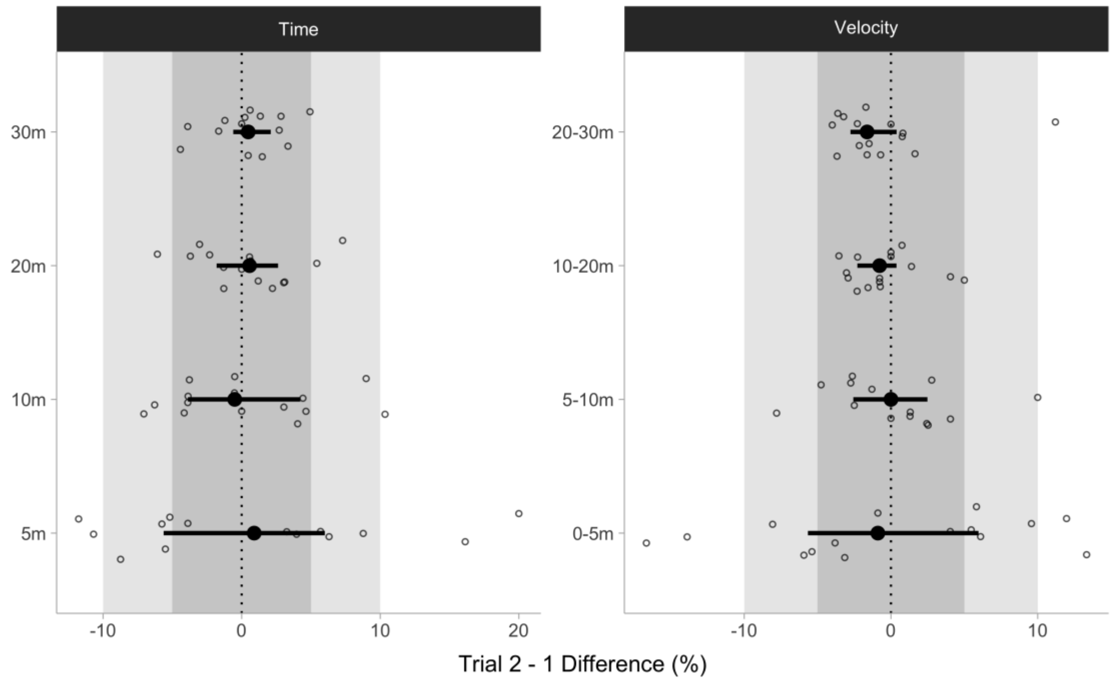


Figure 15. *Percent difference ($\%Diff$) between Trial 2 and Trial 1 for timing gate split times (expressed in s; left panel) and average split velocities (expressed in ms^{-1}; right panel). Grey bars represent ±5 and ±10% difference used as a visual anchor. Error bars represent median and 25th and 75th quantiles (i.e., interquartile range).*

Calculated individual percent coefficients of variation ($\%CV$) between trials for 5, 10, 20, and 30 meter marks ranged from 0.45 to 9.10%, 0 to 4.90%, 0 to 3.5%, and 0.00 to 2.40% respectively, while for the average split velocities ranged from 0.45 to 9.10%, 0.00 to 4.80%, 0.00 to 2.40%, 0.00 to 5.30% for 0-5, 5-10, 10-20, and 20-30 m respectively (Figure 16). Besides 5-meter split time and 0-5-meter average velocity, all other individual performance indicators demonstrated $\%CV$ of less than 5%.

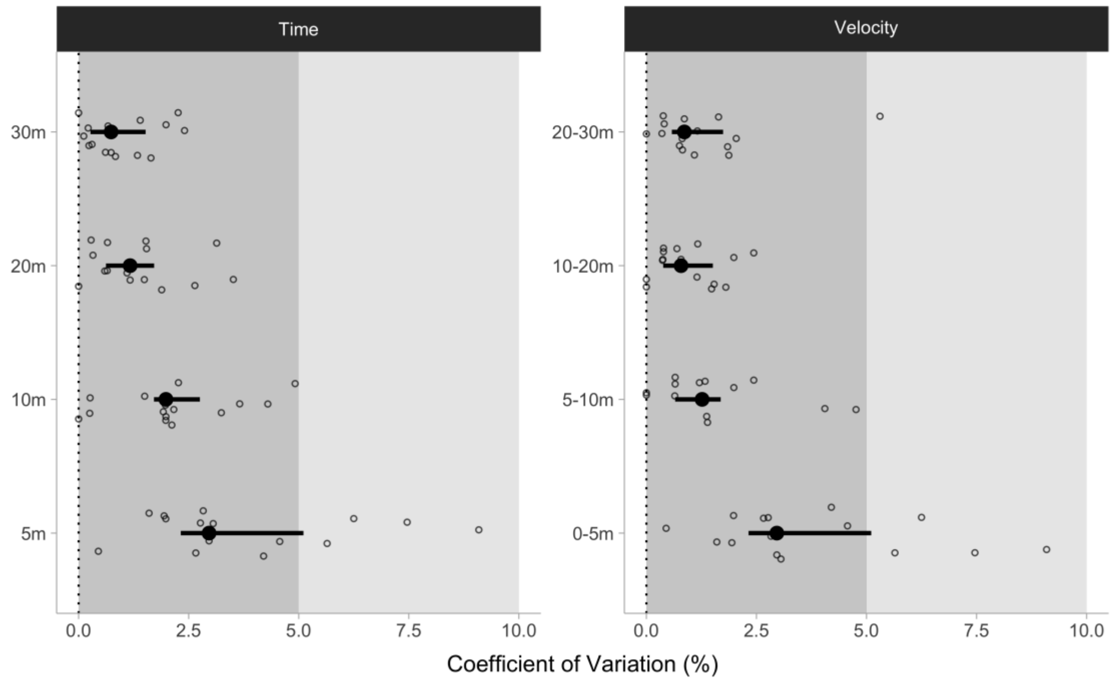


Figure 16. *Percent coefficient of variation (%CV) of timing gate split times (expressed in s; left panel) and average split velocities (expressed in ms^{-1}; right panel). Grey bars represent 5 and 10% difference used as a visual anchor. Error bars represent median and 25th and 75th quantiles (i.e., interquartile range).*

Figure 17 depicts relationship between first (0-5 m) and last (20-30 m) average split velocities using pooled Trial 1 and Trial 2. There was a statistically significant relationship ($p = 0.002$) between average velocity in the last split and average velocity in the initial split, although not strong ($R^2 = 22\%$).

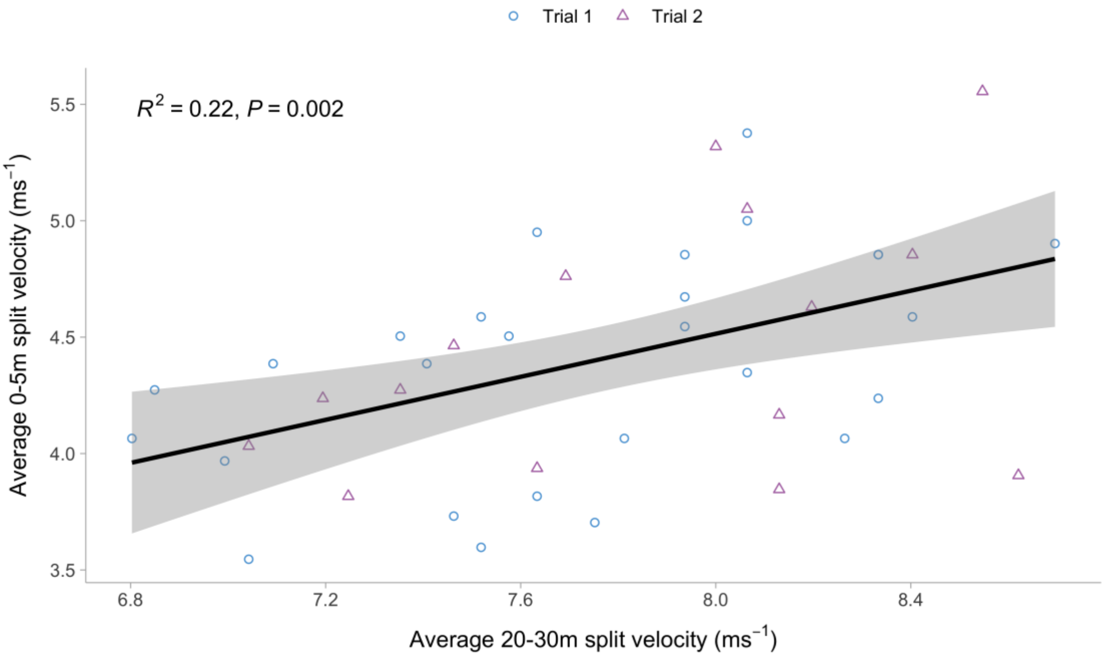


Figure 17. *Relationship between first (0-5 m) and last (20-30 m) average split velocities using pooled Trial 1 (blue ●) and Trial 2 (purple ▲). Shaded area represents 95% confidence interval.* ***Note.*** *R^2 - variance explained; P - $p - value$*

6.2.2.2 Laser and timing gates short sprint estimates

Estimated individual parameter values across Trail 1 and Trial 2 for the laser gun, *No Correction*, *Fixed +0.3s TC*, *Estimated TC*, *Fixed 0.5m FD*, and *Estimated FD* models ranged from 6.60 to 9.68 ms^{-1} for MSS, from 0.36 to 2.13 seconds for TAU, from 4.18 to 23.17 ms^{-2} for MAC, and from 8.49 to 48.2 Wkg^{-1} for $PMAX$ parameter. Figure 18 illustrates these individual parameter values together with their summaries using *median* and 25th and 75th quantiles depicted as horizontal error bars. Visual inspection of Figure 18 indicated that parameter estimates of the *No Correction* demonstrated different values, particularly for the TAU, MAC, and $PMAX$ parameters.

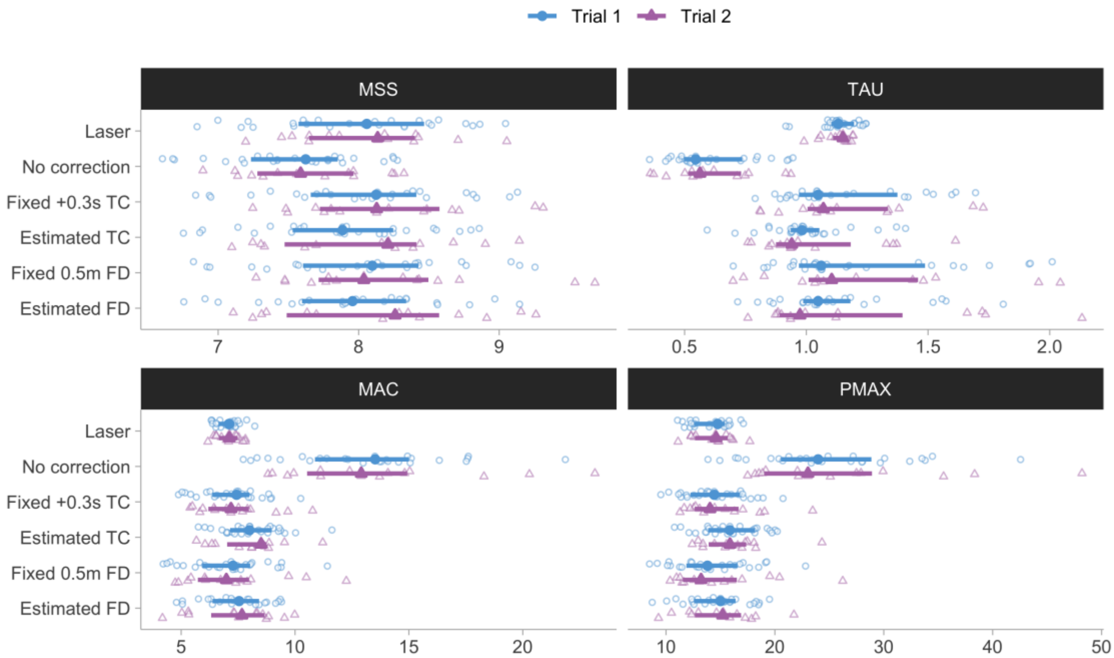
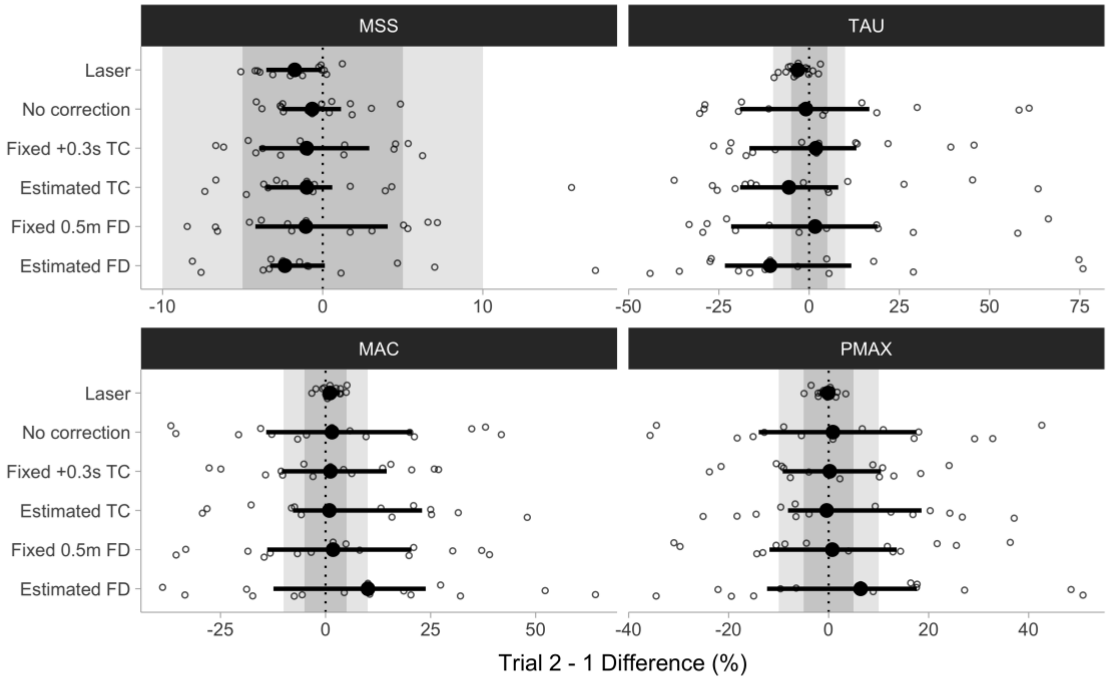
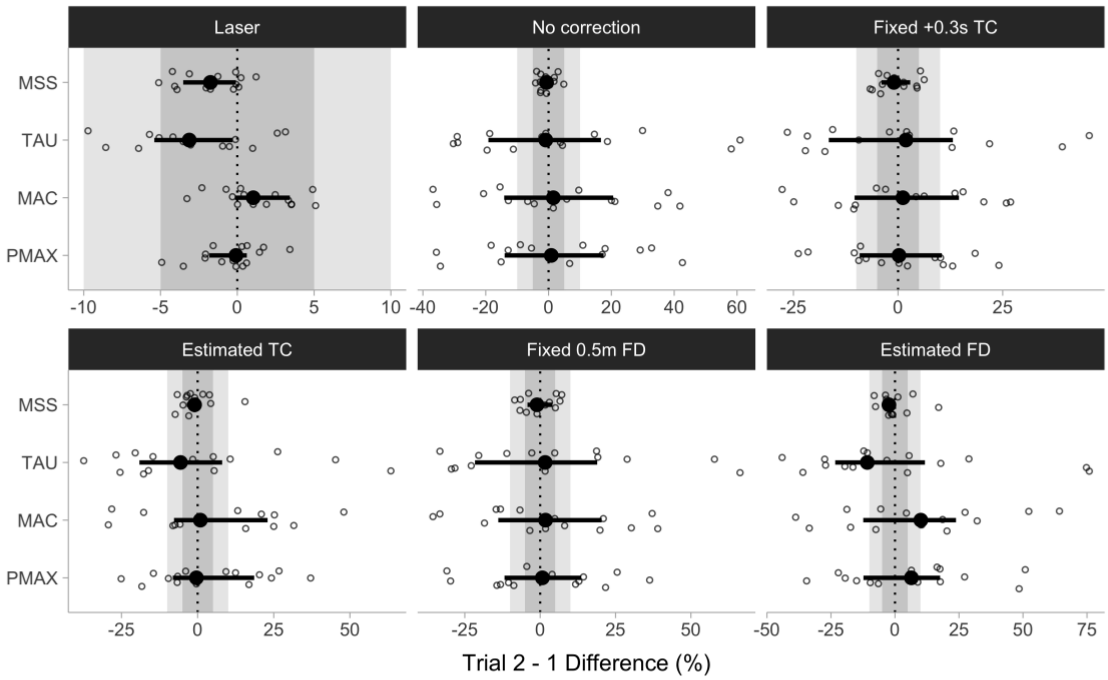


Figure 18. *Short sprint parameter values for Trial 1 (blue ●) and Trial 2 (purple ▲) estimated using (1) Laser, (2) No Correction, (3) Fixed +0.3s time correction (Fixed +0.3s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models. Error bars represent median and 25th and 75th quantiles (i.e., interquartile range).* ***Note.*** *MSS – maximum sprinting speed (expressed in* ms^{-1}*); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in* ms^{-2}*); PMAX – maximal relative power (expressed in* Wkg^{-1}*)*

Estimated individual percent differences ($\%Diff$) between trials for the laser gun, *No Correction*, *Fixed +0.3s TC*, *Estimated TC*, *Fixed 0.5m FD*, and *Estimated FD* models ranged from -8.46 to 17.00% for MSS; from -44.07 to 75.90% for TAU; from -38.78 to 64.20% for MAC; and from -35.71 to 50.90% for $PMAX$ parameter. These individual percent difference values are illustrated in Figure 19 together with their summaries using $median$ and 25th and 75th quantiles depicted as horizontal error bars. Visual inspection of Figure 19 indicated that individual $\%Diff$ values for only the MSS parameter were within -10 and 10% across all models, as well as for all parameters estimated using the laser gun.



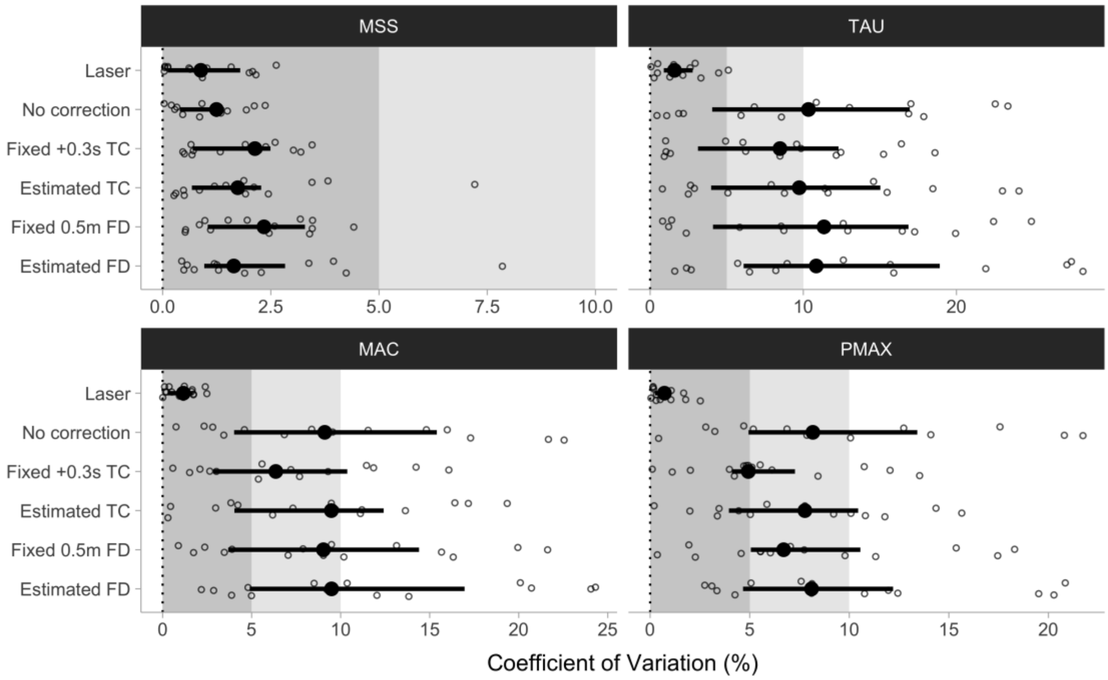
(a) Facets organized using short sprint parameters



(b) Facets organized using models

***Figure 19**. Short sprint parameters percent difference ($\%Diff$) between Trial 2 and Trial 1 estimated using (1) Laser, (2) No Correction, (3) Fixed +0.3s time correction (Fixed +0.3s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models. Grey bars represent ±5 and ±10% difference used as a visual anchor. Error bars represent median and 25th and 75th quantiles (i.e., interquartile range). **Note.** MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

Estimated individual percent coefficients of variation (%CV) for the laser gun, *No Correction*, *Fixed +0.3s TC*, *Estimated TC*, *Fixed 0.5m FD*, and *Estimated FD* models ranged from 0.03 to 7.80% for MSS; from 0.06 to 28.30% for TAU; from 0.01 to 24.30% for MAC; and from 0.04 to 21.70% for $PMAX$ parameter. Figure 20 illustrates individual %CV values together with their summaries using *median* and 25th and 75th quantiles depicted as horizontal error bars. Visual inspection of Figure 20 indicated that individual %CV values for only the MSS parameter were lower than 5% across all models, as well as for all parameters estimated using the laser gun.



(a) Facets organized using short sprint parameters

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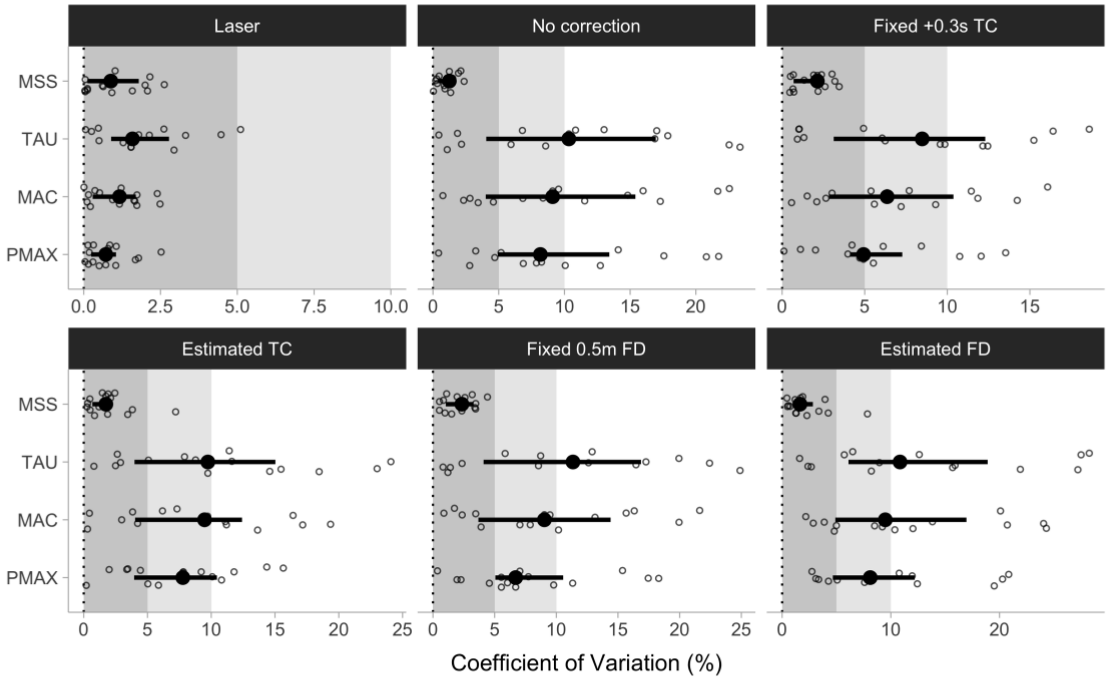


(b) Facets organized using models

Figure 20. *Short sprint parameters percent coefficient of variation (%CV) between Trial 1 and Trial 2 estimated using (1) Laser, (2) No Correction, (3) Fixed +0.3s time correction (Fixed +0.3s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models. Grey bars represent 5 and 10% difference used as a visual anchor. Error bars represent median and 25th and 75th quantiles (i.e., interquartile range).* ***Note.*** *MSS – maximum sprinting speed (expressed in* ms^{-1}*); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in* ms^{-2}*); PMAX – maximal relative power (expressed in* Wkg^{-1}*)*

Figure 21 depicts the relationship between estimated MSS and MAC parameters using pooled Trial 1 and Trial 2. There was a statistically significant relationship ($p < 0.001$) between estimated MSS and MAC parameters only for the laser gun, although not strong ($R^2 = 29\%$).

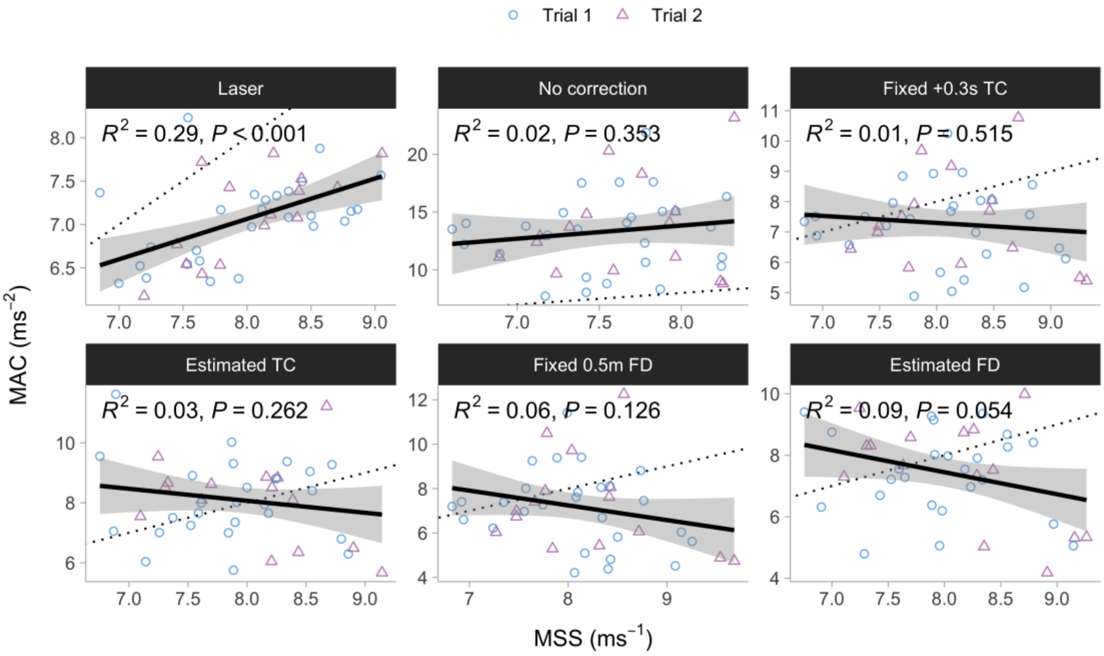


Figure 21. *Relationship between maximum sprinting speed (MSS; expressed in ms^{-1}) and maximum acceleration (MAC; expressed in ms^{-2}) estimated using (1) Laser, (2) No Correction, (3) Fixed +0.3s time correction (Fixed +0.3s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models for pooled Trial 1 (blue ●) and Trial 2 (purple ▲). Shaded areas represent 95% confidence interval. Dotted line represents indentity line (i.e., slope equal to 1).*
Note. *R^2 - variance explained; P - $p - value$*

6.2.2.3 Relationship between MSS estimates and average 20-30m split velocity

Figure 22 illustrates relationship between estimated MSS parameter and last (20-30 m) average split velocity using pooled Trial 1 and Trial 2. There was a statistically significant relationship ($p < 0.001$) between estimated MSS parameter and last average split velocity for all models, with R^2 ranging from 62 to 93%.

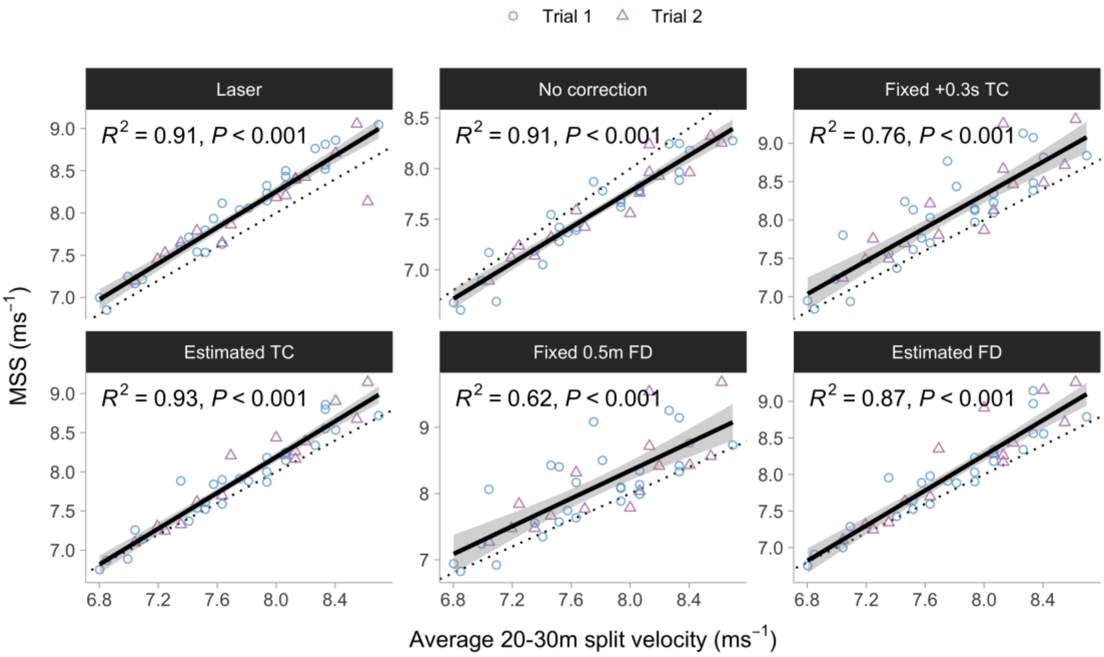


Figure 22. *Relationship between last (20-30 m) average split velocity and maximum sprinting speed parameter (MSS; expressed in ms^{-1}) estimated using (1) Laser, (2) No Correction, (3) Fixed +0.3s time correction (Fixed +0.3s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models for pooled Trial 1 (blue ●) and Trial 2 (purple ▲). Shaded areas represent 95% confidence interval. Dotted line represents indentity line (i.e., slope equal to 1).* ***Note.*** *R^2 - variance explained; P - $p - value$*

6.2.2.4 Relationship between MAC estimates and average 0-5m split velocity

Figure 23 illustrates relationship between estimated MAC parameter and first (0-5 m) average split velocity using pooled Trial 1 and Trial 2. There was a statistically significant relationship ($p < 0.05$) between estimated MAC parameter and the first average split velocity for all models except for *Estimated TC* and *Estimated FD* models. For models with statistically significant relationship, R^2 ranged from 15 to 96%.

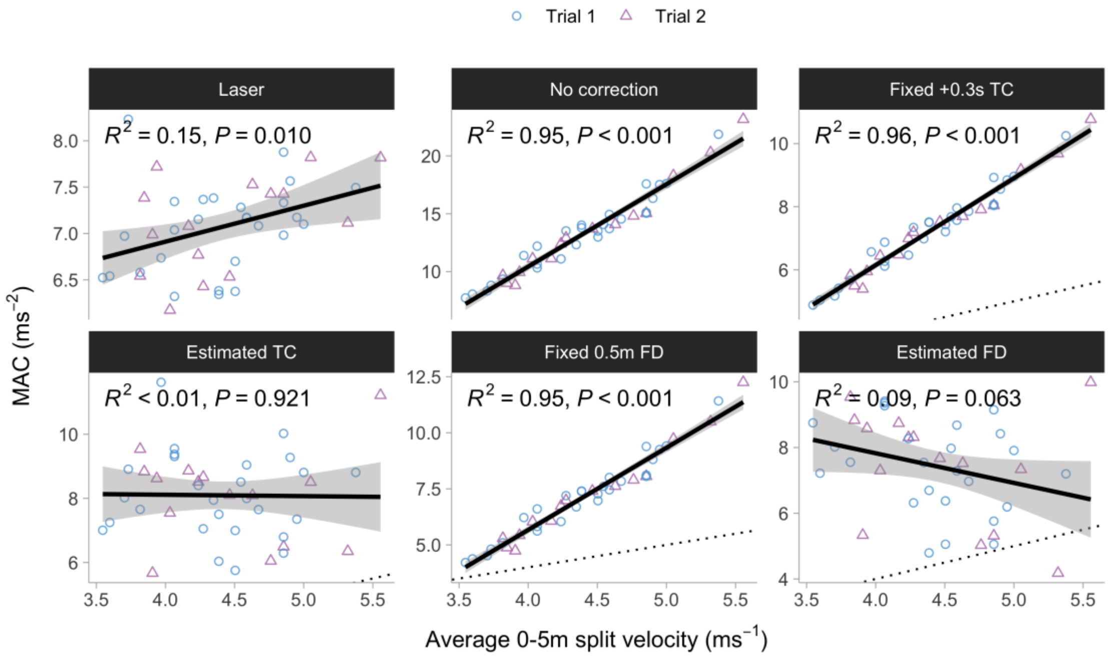


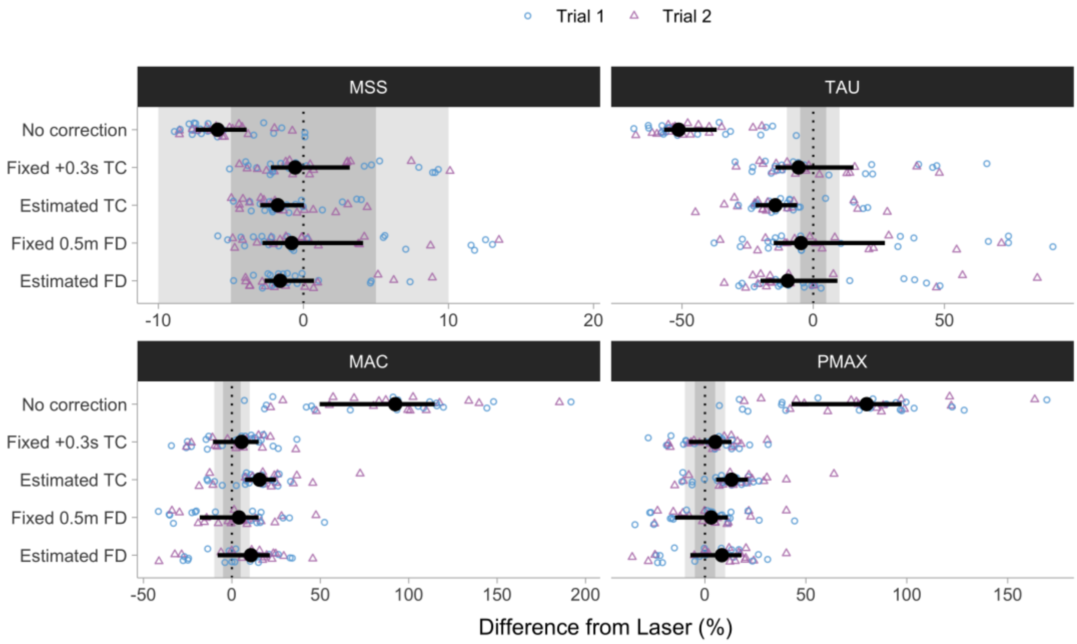
Figure 23. *Relationship between first (0-5 m) average split velocity and maximum acceleration parameter (MAC; expressed in ms^{-2}) estimated using (1) Laser, (2) No Correction, (3) Fixed +0.3s time correction (Fixed +0.3s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models for pooled Trial 1 (blue ●) and Trial 2 (purple ▲). Shaded areas represent 95% confidence interval. Dotted line represents indentity line (i.e., slope equal to 1).* ***Note.*** *R^2 - variance explained; P - $p - value$*

6.2.3 Agreement between Laser and Timing Gates models

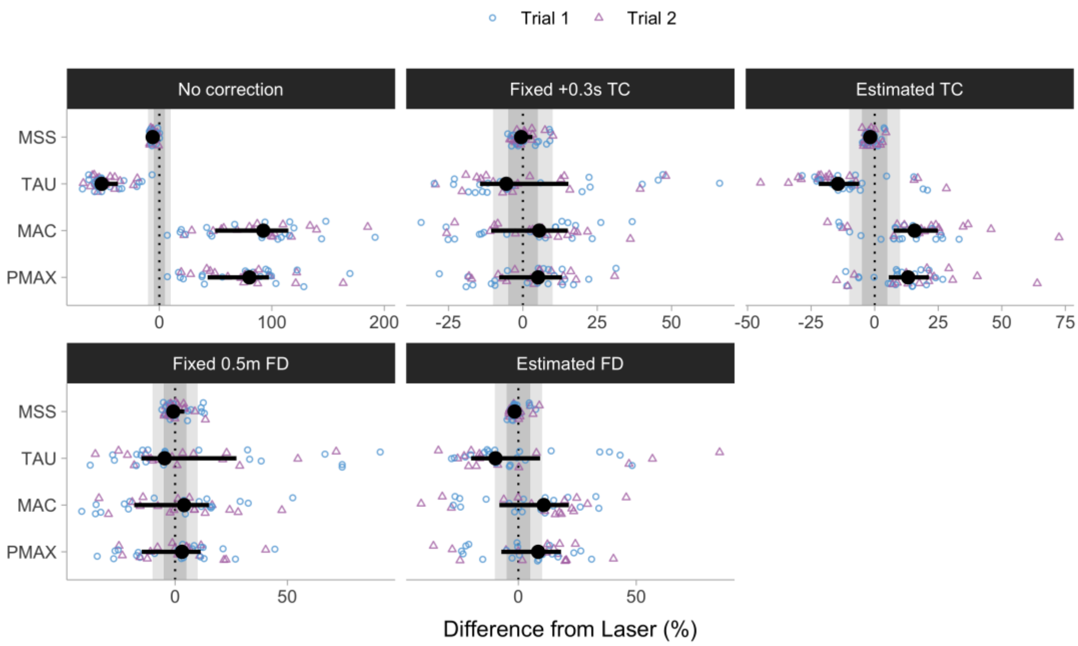
6.2.3.1 Individual agreement using percent difference

Pooled (i.e., Trial 1 and Trial 2 combined) individual parameter agreement using percent difference ($\%Diff$) between laser gun and timing gates estimates for the *No Correction* model ranged from -69.0 to 196.3%, for the *Fixed +0.3s TC* model ranged from -34.2 to 66.2%, for the *Estimated TC* model ranged from -44.9 to 72.5%, for the *Fixed 0.5m FD* model ranged from -41.6 to 91.3%, and for the *Estimated FD* model ranged from -41.3 to 85.4%.

Figure 24 illustrates individual $\%Diff$ values together with their summaries using *median* and 25th and 75th quantiles depicted as horizontal error bars. Visual inspection of Figure 24 indicated that *MSS* parameter demonstrated the highest agreement with the laser across all timing gate models, ranging from -8.9 to 19.0%, while the *MAC* parameter demonstrated the lowest agreement with the percent difference ranging from -41.6 to 196.3%.



(a) Facets organized using short sprint parameters



(b) Facets organized using models

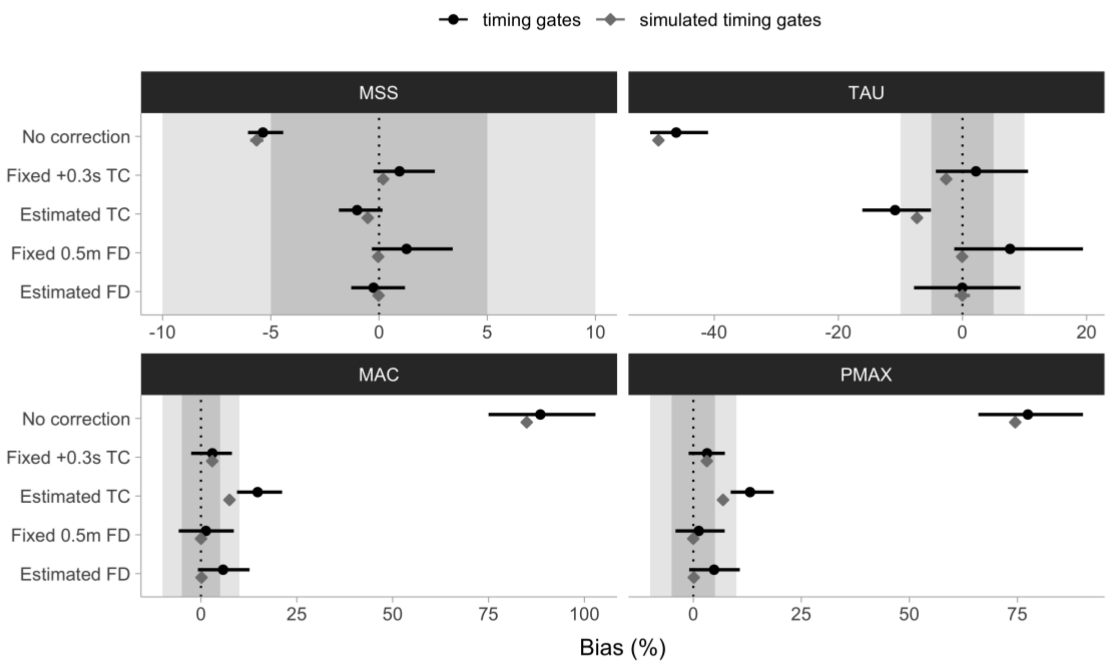
Figure 24. *Short sprint parameters agreement between Laser and (1) No Correction, (2) Fixed +0.3s time correction (Fixed +0.3s TC), (3) Estimated time correction (Estimated TC), (4) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (5) Estimated flying start distance (Estimated FD) models, estimated using percent difference ($\%Diff$). Pooled Trial 1 (blue ●) and Trial 2 (purple ▲) data set were utilized. Grey bars represent ±5 and ±10% difference used as a visual anchor. Error bars represent median and 25th and 75th quantiles (i.e., interquartile range).* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

6.2.3.2 *Estimated bias*

Estimated mean percent difference (%$Bias$) between laser gun and timing gates parameter estimates, using pooled Trial 1 and Trial 2, for the *No Correction* model ranged from -46.1 to 88.5%, for the *Fixed +0.3s TC* model ranged from 0.9 to 3.2%, for the *Estimated TC* model ranged from -10.9 to 14.8%, for the *Fixed 0.5m FD* model ranged from 1.3 to 7.7%, and for the *Estimated FD* model ranged from -0.3 to 5.8%.

MSS parameter demonstrated the lowest bias across all timing gate models, ranging from -5.4 to 1.3%, while the MAC parameter demonstrated the highest bias ranging from 1.3 to 88.5%.

Figure 25 depicts the estimated %$Bias$ and accompanying 95% confidence intervals as error bars. Visual inspection of Figure 25 demonstrated that (1) simulated timing gates and observed data confidence intervals overlap or touch for all models (apart from the *Estimated TC* model for the MAC and $PMAX$ parameters), (2) the *No Correction* model confidence intervals excluded zero line for all parameters, and (3) *Estimated TC* model confidence intervals excluded zero line for all parameters except MSS.



(a) Facets organized using short sprint parameters

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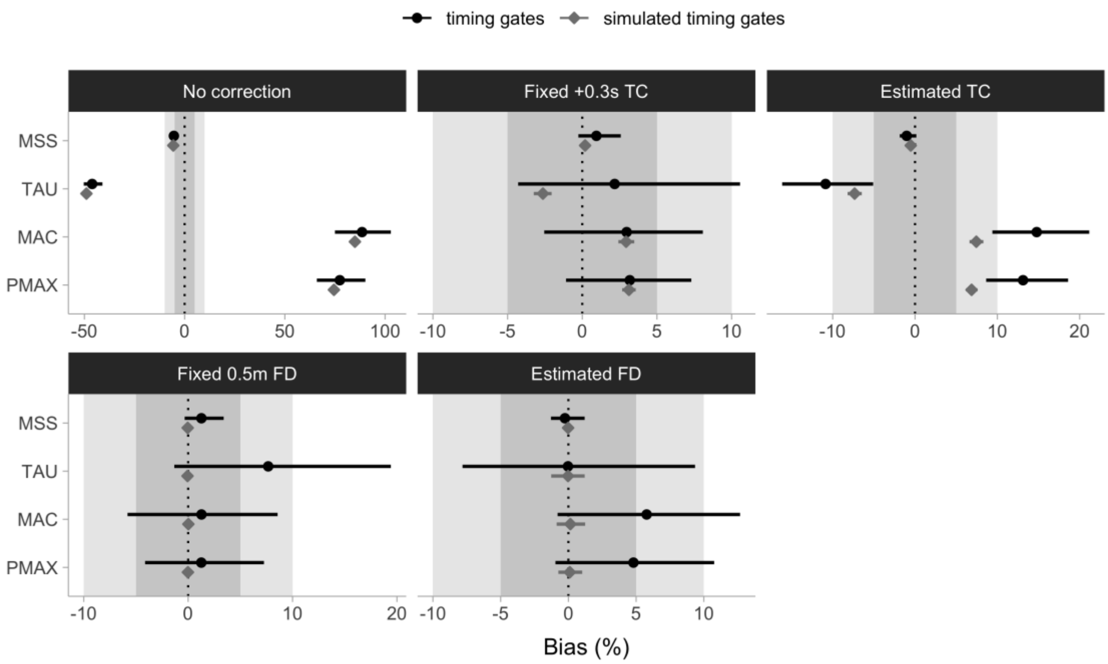


(b) Facets organized using models

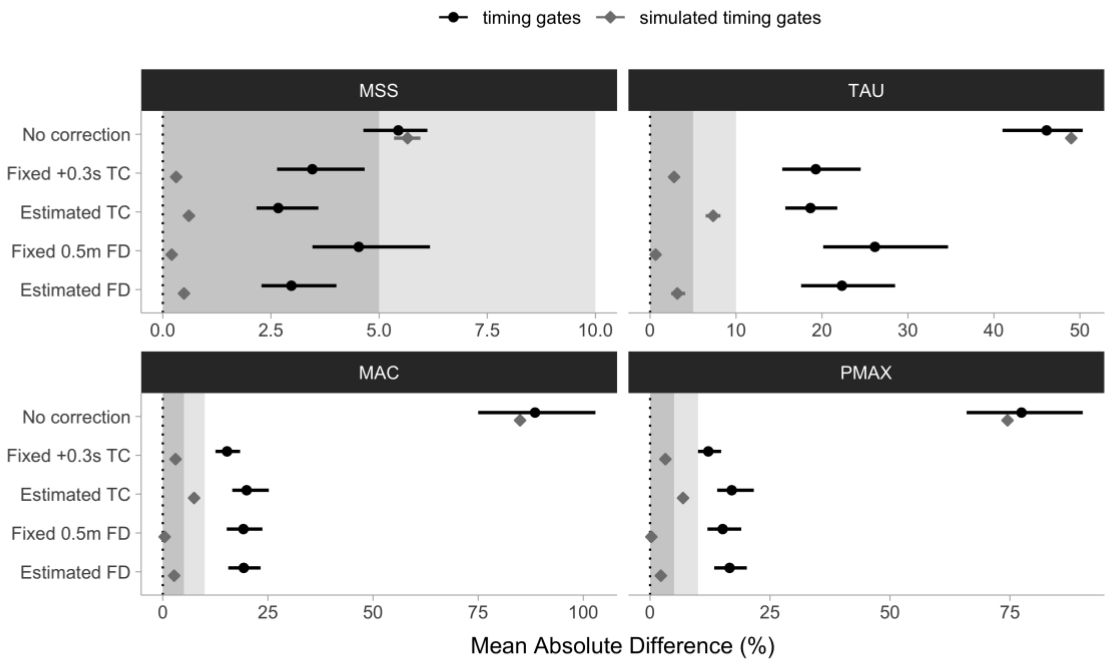
Figure 25. *Estimated short sprint parameters percent bias (i.e., mean difference) between Laser and (1) No Correction, (2) Fixed +0.3s time correction (Fixed +0.3s TC), (3) Estimated time correction (Estimated TC), (4) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (5) Estimated flying start distance (Estimated FD) models, for both observed timing gate split times (black ●), and simulated timing gate split times (grey ◆). Simulated timing gate split times are generated using Laser estimates as a generative model, assuming 0.5m flying distance, and 0.01s time rounding. Simulated timing gates models thus represent expected bias, given theoretical assumptions. Pooled data set (i.e., Trial and Trial 2) were utilized. Grey bars represent ±5 and ±10% difference used as visual anchors. Error bars represent 95% bias-corrected and accelerated (BCa) 2,000 resamples bootstrap confidence intervals.* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

6.2.3.3 Estimated mean absolute difference

Estimated mean percent absolute difference ($\%MAD$) between laser gun and timing gates parameter estimates, using pooled Trial 1 and Trial 2, for the *No Correction* model ranged from 5.4 to 88.5%, for the *Fixed +0.3s TC* model ranged from 3.5 to 19.3%, for the *Estimated TC* model ranged from 2.7 to 19.9%, for the *Fixed 0.5m FD* model ranged from 4.5 to 26.2%, and for the *Estimated FD* model ranged from 3 to 22.3%.

MSS parameter demonstrated the lowest $\%MAD$ across all timing gate models, ranging from 2.7 to 5.4%, while the MAC parameter demonstrated the highest $\%MAD$ ranging from 15.3 to 88.5%.

Figure 26 depicts the estimated $\%MAD$ and accompanying 95% confidence intervals as error bars. Visual inspection of Figure 25 demonstrated that (1) only the *No Correction* model confidence intervals overlap for the simulated and observed data, while all other models demonstrated higher $\%MAD$ than expected by simulation, (2) only the MSS parameter demonstrated $\%MAD$ below 5% for all models except for the *No Correction* and *Fixed 0.5m FD* models, while all other parameters demonstrated $\%MAD$ higher than 10%.



(a) Facets organized using short sprint parameters

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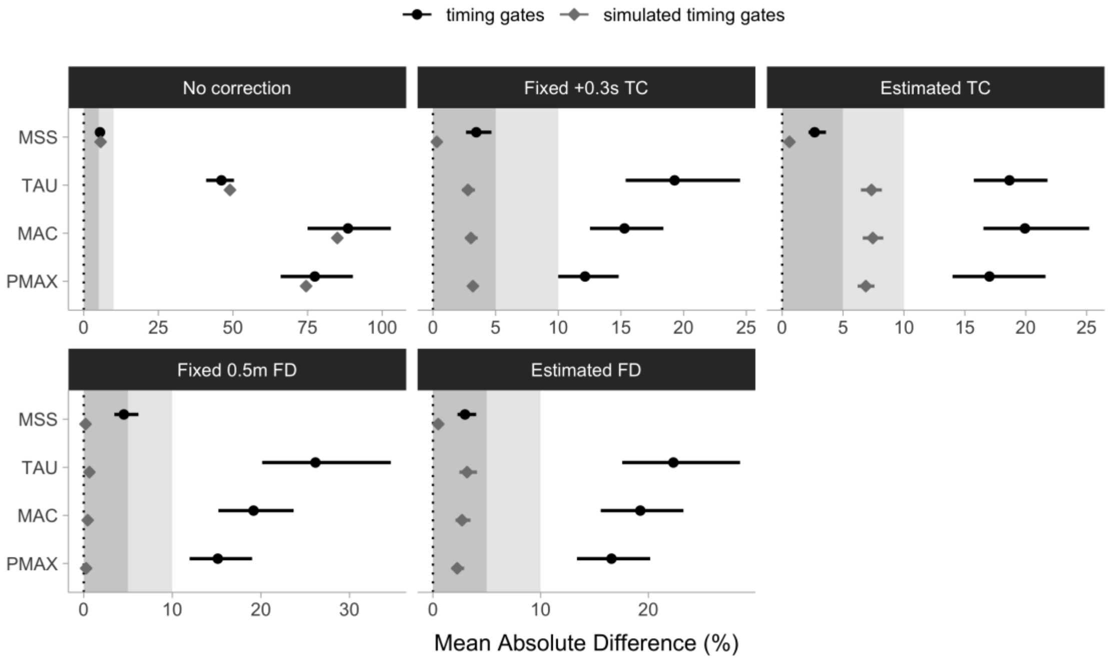


(b) Facets organized using models

***Figure 26**. Estimated short sprint parameters percent mean absolute difference (%MAD) between Laser and (1) No Correction, (2) Fixed +0.3s time correction (Fixed +0.3s TC), (3) Estimated time correction (Estimated TC), (4) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (5) Estimated flying start distance (Estimated FD) models, for both observed timing gate split times (black ●), and simulated timing gate split times (grey ◆). Simulated timing gate split times are generated using Laser estimates as a generative model, assuming 0.5m flying distance, and 0.01s time rounding. Simulated timing gates models thus represent expected %MAD, given theoretical assumptions. Pooled data set (i.e., Trial and Trial 2) were utilized. Grey bars represent 5 and 10 %MAD used as a visual anchor. Error bars represent 95% bias-corrected and accelerated (BCa) 2,000 resamples bootstrap confidence intervals. **Note.** MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

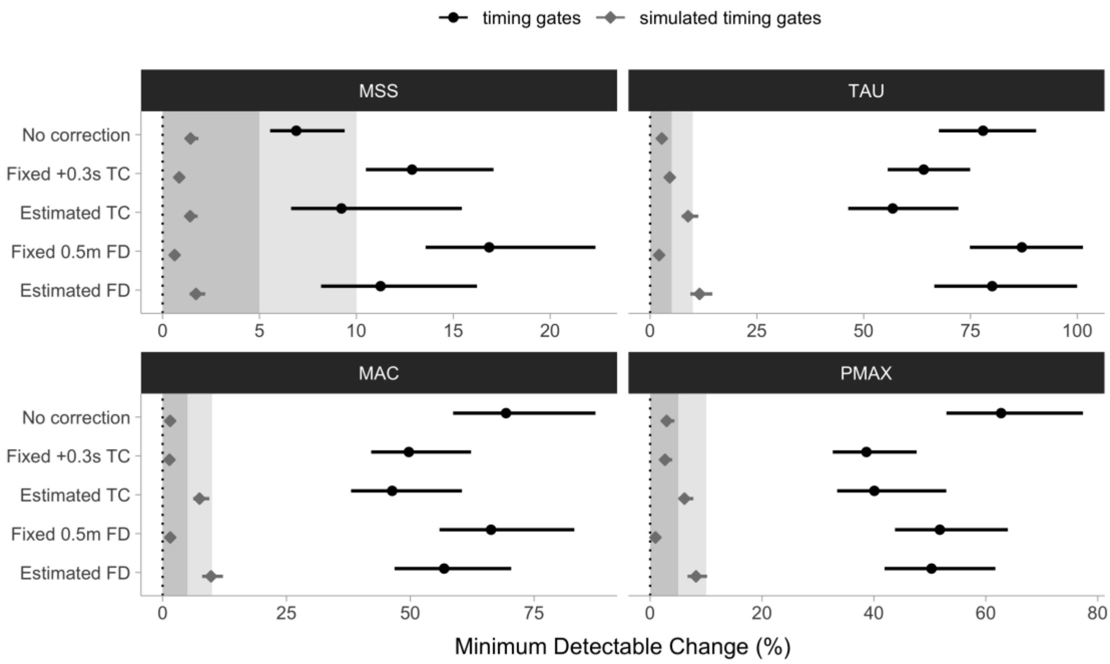
6.2.4 Minimal detectable change

6.2.4.1 MDC using an agreement with Laser

Estimated percent minimum detectable change (%MDC_{95}) using an agreement with the laser gun and pooled Trial 1 and Trial 2, for the *No Correction* model ranged from 6.9 to 77.9%, for the *Fixed +0.3s TC* model ranged from 12.9 to 64.0%, for the *Estimated TC* model ranged from 9.2 to 56.8%, for the *Fixed 0.5m FD* model ranged from 16.9 to 87.0%, and for the *Estimated FD* model ranged from 11.2 to 80.1%.

MSS parameter demonstrated the lowest $\%MDC_{95}$ across all timing gate models, ranging from 6.9 to 16.9%, while the TAU parameter demonstrated the highest $\%MDC_{95}$ ranging from 56.8 to 87%.

Figure 27 depicts the estimated $\%MDC_{95}$ and accompanying 95% confidence intervals as error bars. Visual inspection of Figure 27 showed that (1) $\%MDC_{95}$ was lowest for the MSS parameter, particularly the *No Correction* model, and that (2) all other parameters and models demonstrated $\%MDC_{95}$ beyond what was expected by the simulated data set.



(a) Facets organized using short sprint parameters

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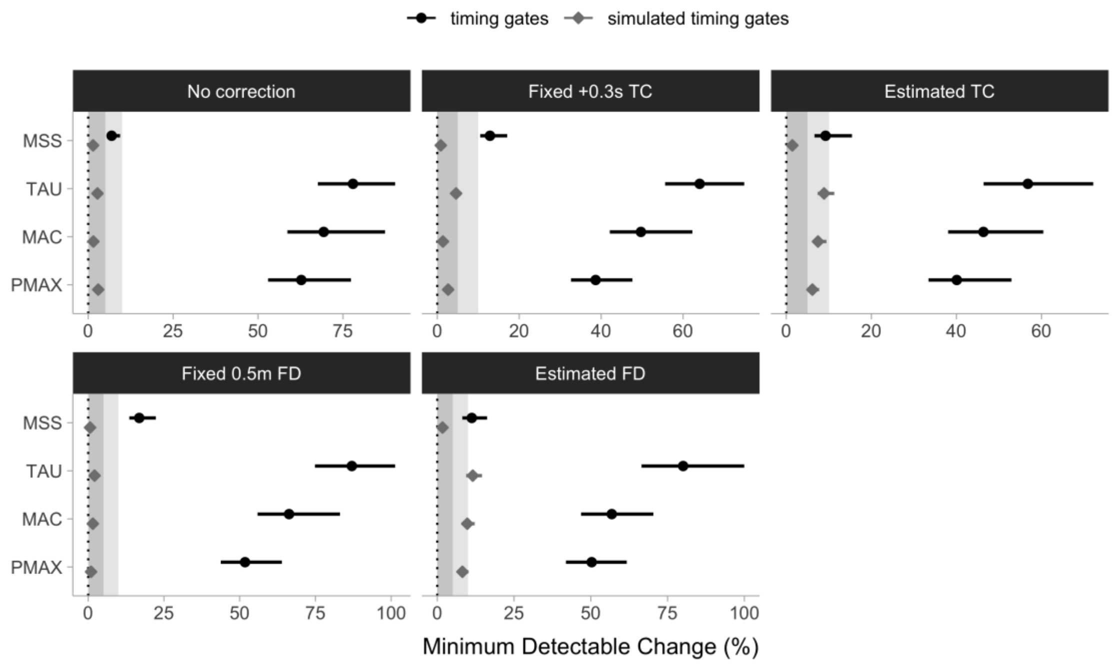


(b) Facets organized using models

Figure 27. *Estimated short sprint parameters minimal detectable change using 95% confidence level (%$MDCs_{95}$) for both observed timing gate split times (black ●), and simulated timing gate split times (grey ◆). Method for estimating %$MDCs_{95}$ utilized pooled Trial 1 and Trial 2 linear regression percent residual standard error (%RSE; Equation 11) between Laser and (1) No Correction, (2) Fixed +0.3s time correction (Fixed +0.3s TC), (3) Estimated time correction (Estimated TC), (4) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (5) Estimated flying start distance (Estimated FD) models. Simulated timing gate split times are generated using Laser estimates as a generative model, assuming 0.5m flying distance, and 0.01s time rounding. Simulated timing gates models represent expected %$MDCs_{95}$, given theoretical assumptions. Grey bars represent 5 and 10 %$MDCs_{95}$ used as a visual anchor. Error bars represent 95% bias-corrected and accelerated (BCa) 2,000 resamples bootstrap confidence intervals.* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

6.2.4.2 MDC using change scores

Estimated percent minimum detectable change (%MDC_{95}) for the timing gate splits using the change between Trial 1 and Trial 2 ranged from 5.0 to 17.2%, with 5-meter split time demonstrating the highest value, and a 30-meter demonstrating the lowest value (Figure 28). Estimated %MDC_{95} for the average split velocity ranged from 4.6 to 17.6%, with 0-5-meter split time demonstrating the highest value, and 10-20-meter split demonstrating the lowest value (Figure 28). Visual inspection of the 95% confidence intervals depicted in Figure 28 showed all estimates, except for the average 20-30 and 10-20-meter split velocity, to be larger than expected by simulation.

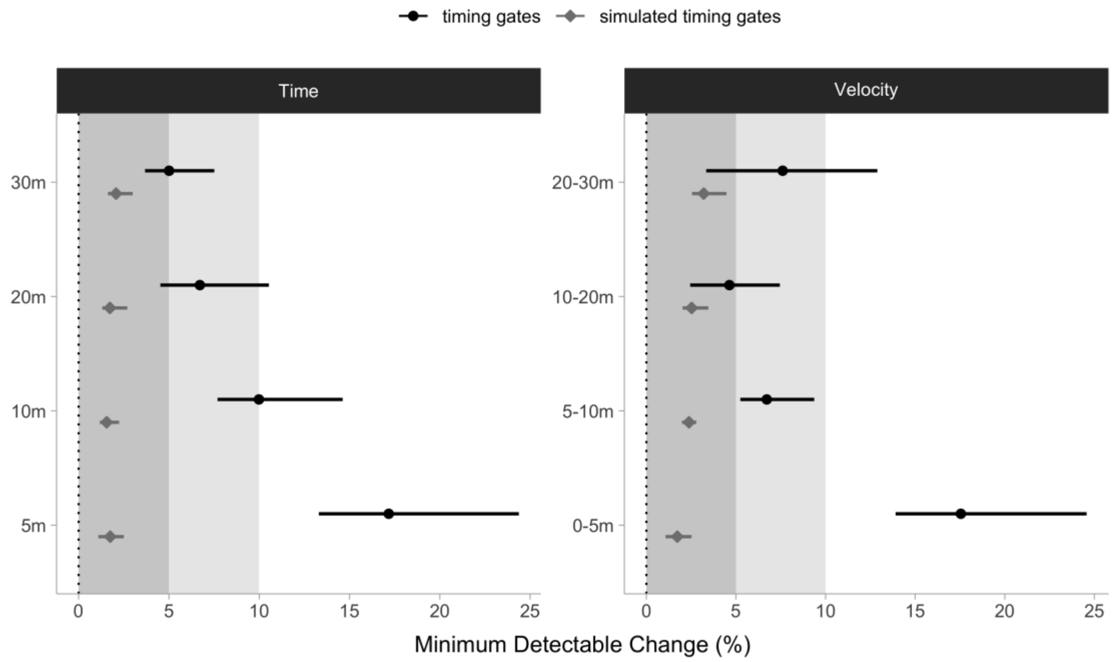
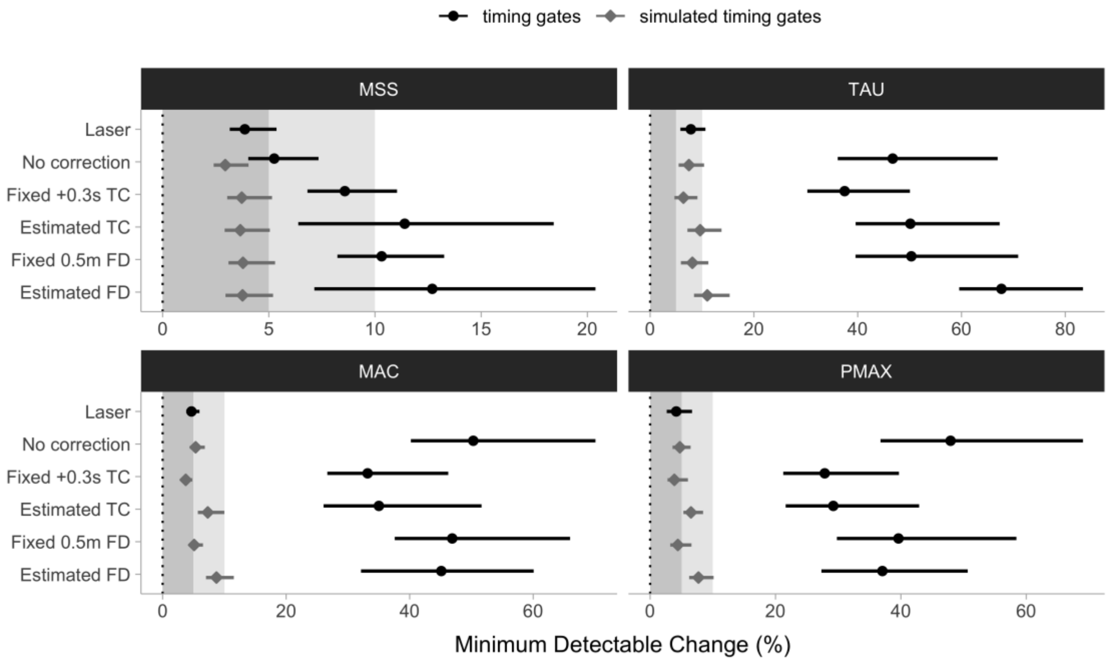


Figure 28. *Estimated minimal detectable change using 95% confidence level (%$MDCs_{95}$) for split times (expressed in s; left panel) and average split velocities (expressed in ms^{-1}; right panel) for both observed timing gate split times (black ●), and simulated timing gate split times (grey ◆). Method for estimating %$MDCs_{95}$ utilized linear regression percent residual standard error (%RSE; Equation 11) between Trial 1 and Trial 2. Grey bars represent 5 and 10 %$MDCs_{95}$ used as a visual anchor. Error bars represent 95% bias-corrected and accelerated (BCa) 2,000 resamples bootstrap confidence intervals.*

Estimated percent minimum detectable change (%MDC_{95}) using the change between Trial 1 and Trial 2, for the laser gun ranged from 3.9 to 7.8%, for the *No Correction* model ranged from 5.3 to 50.3%, for the *Fixed +0.3s TC* model ranged from 8.6 to 37.5%, for the *Estimated TC* model ranged from 11.4 to 50.1%, for the *Fixed 0.5m FD* model ranged from 10.3 to 50.3%, and for the *Estimated FD* model ranged from 12.7 to 67.7%.

MSS parameter demonstrated the lowest %MDC_{95} across all timing gate models, ranging from 5.3 to 12.7%, while the TAU parameter demonstrated the highest %MDC_{95} ranging from 37.5 to 67.7%.

Figure 27 depicts the estimated %MDC_{95} and accompanying 95% confidence intervals as error bars. Visual inspection of Figure 27 showed that (1) %MDC_{95} was lowest for the MSS parameter, particularly the *No Correction* model, and that (2) all other parameters and models demonstrated %MDC_{95} beyond what was expected by the simulated data set.



(a) Facets organized using short sprint parameters

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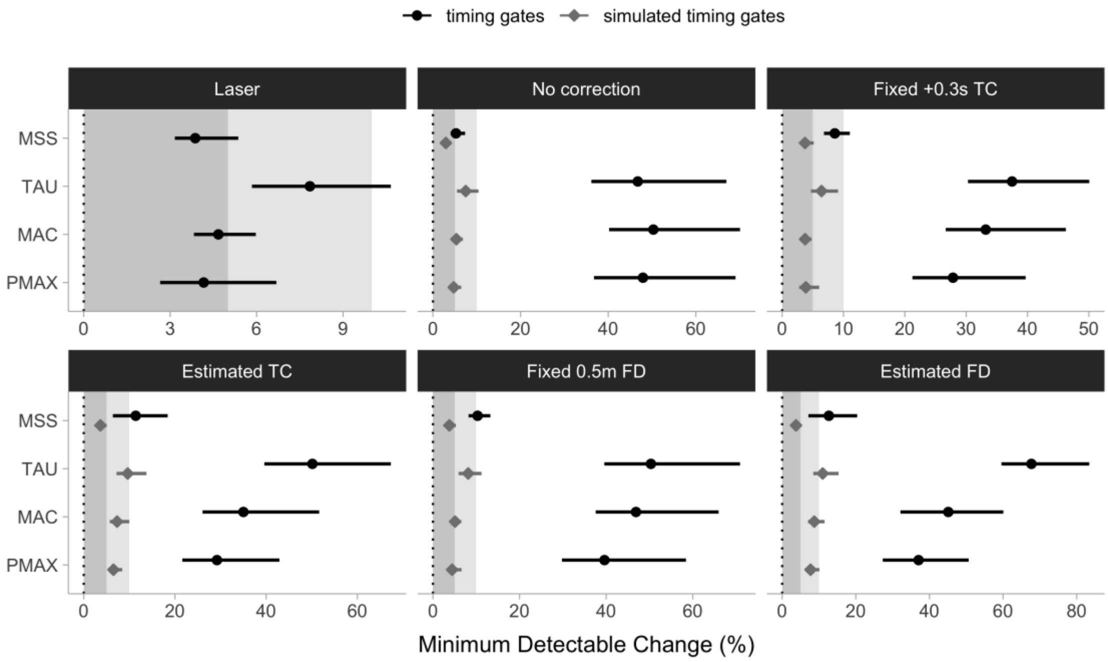

(b) Facets organized using models

Figure 29. *Estimated short sprint parameters minimal detectable change using 95% confidence level (%$MDCs_{95}$) for both observed timing gate split times (black ●), and simulated timing gate split times (grey ◆) using (1) Laser, (2) No Correction, (3) Fixed +0.3s time correction (Fixed +0.3s TC), (4) Estimated time correction (Estimated TC), (5) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (6) Estimated flying start distance (Estimated FD) models. Method for estimating %$MDCs_{95}$ utilized linear regression percent residual standard error (%RSE; Equation 11) between Trial 1 and Trial 2. Simulated timing gate split times are generated using Laser estimates as a generative model, assuming 0.5m flying distance and 0.01s time rounding. Simulated timing gates models represent expected %$MDCs_{95}$, given theoretical assumptions. Grey bars represent 5 and 10 %$MDCs_{95}$ used as a visual anchor. Error bars represent 95% bias-corrected and accelerated (BCa) 2,000 resamples bootstrap confidence intervals.* ***Note.*** *MSS – maximum sprinting speed (expressed in ms^{-1}); TAU – relative acceleration (expressed in seconds); MAC – maximum acceleration (expressed in ms^{-2}); PMAX – maximal relative power (expressed in Wkg^{-1})*

Figure 30 depicts the combined estimated %MDC_{95} using an agreement with a laser gun and change score analysis methods for easier interpretation. The left panel titled *Acceleration* in Figure 30 represents *maximum acceleration indices* and combines estimated %MDC_{95} using 0-5 meters average velocity for the splits and maximum-acceleration (MAC) parameter for the other models. The right panel titled *Max Speed* in Figure 30 represents *maximum speed indices* and combines estimated %MDC_{95} using 20-30 meters average velocity for the splits and maximum-sprinting-speed (MSS) parameter for the other models.

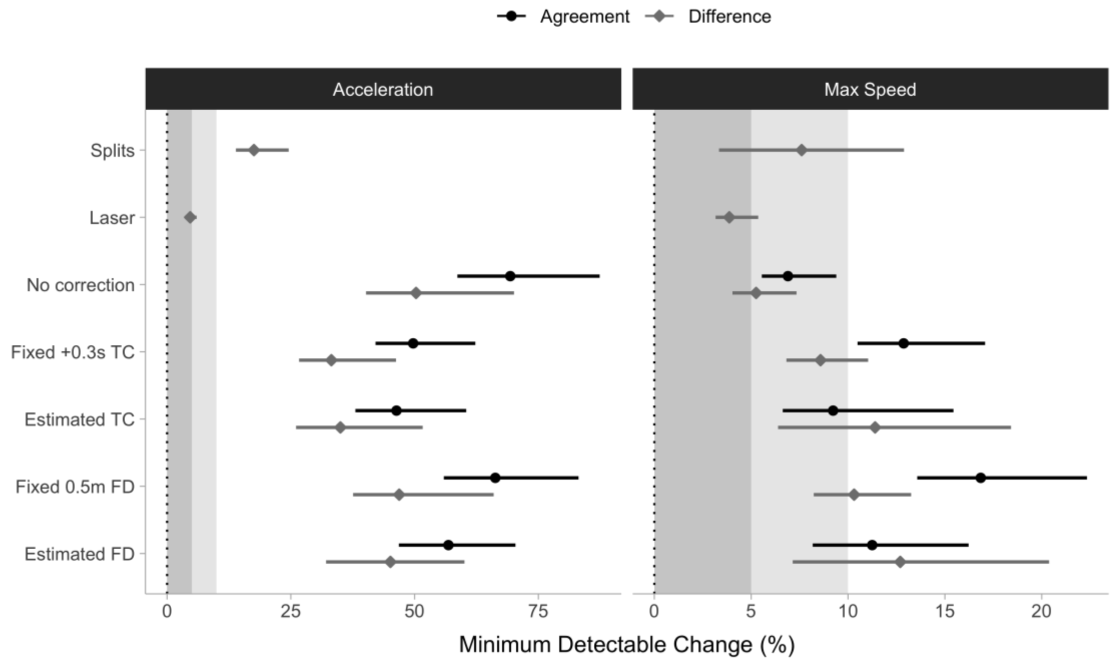

Figure 30. *Combined estimated percent minimal detectable change using 95% confidence level ($\%MDCs_{95}$) using the agreement with laser gun (black ●) and change scores between Trial 1 and Trial 2 (grey ◆) for the (1) split times, (2) Laser, (3) No Correction, (4) Fixed +0.3s time correction (Fixed +0.3s TC), (5) Estimated time correction (Estimated TC), (6) Fixed 0.5m flying start distance (Fixed 0.5m FD), and (7) Estimated flying start distance (Estimated FD) models. The Acceleration panel depicts $\%MDCs_{95}$ using 0-5 meters average velocity for the splits and maximum-acceleration (MAC) parameter for the other models. The Max Speed panel depicts $\%MDCs_{95}$ using 20-30 meters average velocity for the splits and maximum-sprinting-speed (MSS) parameter for the other models. Grey bars represent 5 and 10 $\%MDCs_{95}$ used as a visual anchor. Error bars represent 95% bias-corrected and accelerated (BCa) 2,000 resamples bootstrap confidence intervals.*

6.3 Discussion

6.3.1 Descriptive analysis

Individual percent coefficient of variation ($\%CV$) demonstrated higher variability and higher *median* value for the 5-meter split times compared to the 30-meter, as well as for the initial versus last average split velocity (Figure 16). This was also a pattern demonstrated in parameters' $\%CV$ across timing gates models, with MSS parameter showing smaller *median* value as well as the *interquartile range* (IQR) compared to the MAC parameter (Figure 20). This suggests that there might be *inherent* issues in estimating *sprint acceleration* compared to the *maximum sprinting speed* traits. This was also reflected in estimating sensitivity to detect changes using the minimal detectable change estimator ($\%MDC_{95}$), in which *sprint acceleration* trait had much lower sensitivity compared to *maximum sprinting speed* when estimated using timing gates models (Figure 30).

Initial and last split average velocity (i.e., 0-5 and 20-30 m) demonstrated a statistically significant relationship ($p = 0.002$), although with low variance explained (R^2 equal to 22%)

(Figure 17). Relationship between estimated MSS and MAC parameters was statistically significant only for the laser gun ($p < 0.001$), although with similar low variance explained (R^2 equal to 29%) (Figure 21). Given these findings, it can be concluded that athletes who are faster, also tend to be faster accelerators on average when estimated with laser and split times.

The relationship between the estimated MSS parameter and the 20-30 meter average split velocity demonstrated statistical significance for all models ($p < 0.001$). This relationship was highest for the *Estimated TC* model (R^2 equal to 93%) and lowest for the *Fixed 0.5m FD* model (R^2 equal to 62%) (Figure 22).

Interestingly, the relationship between estimated MAC parameter and the 0-5 meter average split velocity demonstrated statistical significance ($p < 0.001$) with large variance explained (R^2 over 95%) for the *No Correction*, *Fixed +0.3s TC*, and *Fixed 0.5m FD* models, which are models with two estimated parameters. *Estimated TC* and *Estimated FD* models didn't demonstrate statistical significance. It might be speculated that this is due to three estimated parameters in these models. The laser gun model demonstrated a statistically significant relationship between MAC parameter and the 0-5 meter average split velocity demonstrated ($P = 0.01$), but will low variance explained (R^2 equal to 15%) (Figure 23). It can be speculated that the higher variance explained in the relationship between MAC and 0-5 meter average split velocity with *No Correction*, *Fixed +0.3s TC*, and *Fixed 0.5m FD* models compared to the laser gun is due to the fact that MAC parameter is estimated from the split times themselves, while for the laser gun, MAC is estimated using laser velocity-time trace.

6.3.2 Agreement

Agreement between laser gun and timing gates estimates using the *percent bias* ($\%Bias$, or percent mean difference) estimator demonstrated expected results, given the first part of the study implementing simulation. This was evident using the confidence intervals of the simulated timing gates and observed data being overlapping or touching for all models (apart from the *Estimated TC* model for the MAC and $PMAX$ parameters) (Figure 25).

Using the confidence intervals to judge statistical significance (i.e., with confidence intervals not crossing zero line or other magnitude thresholds; Jovanović (2020b)), the *No Correction* model showed bias involved in all parameters when estimated using a laser gun as the criterion. The *Estimated TC* model also demonstrated statistically significant bias for all parameters except MSS. All other models did not demonstrate statistically significant bias involved when estimating parameters.

Agreement estimated using the *percent mean absolute difference* ($\%MAD$) estimator demonstrated expected results for the *No Correction* model, with overlapping confidence intervals for the simulated and observed data. Every other model demonstrated a higher $\%MAD$ compared to expected values using the simulated data. Of all parameters, only MSS demonstrated high agreement between laser gun and timing gates estimates, using the $\%MAD$ estimator (below 5% for all models except for the *No Correction* and *Fixed 0.5m FD* models). All other parameters demonstrated unsatisfying agreement with the laser gun ($\%MAD$ > 10%) (Figure 26).

6.3.3 Sensitivity

Besides correctly estimating the current values of the short sprint parameters, practitioners are probably more interested in sensitivity to detect changes across time. Two different methods are utilized in this part of the study to estimate this sensitivity. The first method utilized the agreement with the laser gun (i.e., assuming laser gun estimates represent the *true* scores), while the second method utilized the change between trials, essentially adding *intra-session biological variability*.

When using the agreement with the laser gun, MSS parameter showed the highest sensitivity (i.e., lowest $\%MDC_{95}$), and interestingly, it was the highest for the *No Correction* model. All other parameters and models demonstrated an unsatisfying level of sensitivity, beyond what was expected by the simulated data set (Figure 27). The lowest $\%MDC_{95}$ for the MSS parameter estimated with the *No Correction* model might be due to the simplest model utilized, and hence reduced variability in the estimated parameters.

When estimated using the Trial 1 and Trial 2 differences, the highest sensitivity was demonstrated by the laser gun across all parameters, with the MSS parameter showing the highest sensitivity across all models. All models demonstrated higher $\%MDC_{95}$ than expected by the simulation (Figure 29). As explained previously, the split times also demonstrated the lowest sensitivity for the initial split times and average velocity (Figure 28) due to the highest $\%CV$ (Figure 16).

Overall, maximum sprinting speed indicators (i.e., MSS parameter or 20-30-meter average split velocity) demonstrated higher sensitivity than the maximum acceleration indicators (i.e., MAC parameter or 0-5 meter average split velocity) (Figure 30).

7 GENERAL CONCLUSION

Valid and reliable estimation of the short sprint performance is one of the most important athlete profiling components. Acceleration-velocity profile (i.e., MSS and MAC parameters) represents a simple model to describe the kinematic of the short sprint performance. As such, it is attractive to sports practitioners to compare, evaluate, track, and monitor athletes across time and training interventions. Most often, laboratory tools like 3D motion cameras, videos, or laser guns, are not readily available in all but a small number of elite sports teams. Thus, practitioners have been using split times measured using photocell timing gates to estimate maximum acceleration and maximum speed indicators. The recent development of the AVP model aimed to simplify this pursuit by consolidating various split time analyses into a simple and intuitive two-parameter model, where MAC parameter represents indicator of maximum acceleration characteristics and MSS parameter represents indicator of the maximum sprinting speed characteristic.

The results of the current study question the validity, reliability, as well as sensitivity of the AVP, estimated using timing gates, even with the novel correction models that were introduced. Maximum acceleration indicators (i.e., MAC and 0-5 m average split velocity) demonstrated low agreement when compared to the laser gun, as well as unsatisfactory sensitivity to detect changes. Maximum sprinting speed indicators (i.e., MSS and 20-30 m average split velocity) demonstrated much better agreement with the laser gun, and satisfactory sensitivity to detect changes. Interestingly, the results indicated that the simplest *No Correction* model demonstrated the highest sensitivity to detect changes in MSS compared to all other timing gate models, although showing significant bias.

Thus, practitioners should be wary of using timing gates to estimate maximum acceleration traits and changes in their respective levels.

The main limit of the second part of the study involving athletes is utilizing only one starting distance (i.e., 0.5 m from the initial timing gate) and performing only two sprint trials in a single day. However, this method is ecologically valid, since it is the most common method of measuring short sprint performance by practitioners in team sports (Haugen et al., 2020d, 2020b; T. Haugen & Buchheit, 2016b; Tillaar et al., 2022).

Future work should involve a similar study done with multiple sprints performed with different starting distances (i.e., on line, 0.5 and 1 meter from the initial timing gate), positions (i.e., standing versus three-point or block start), triggering devices (foot pod, hand pod, etc.), types of timing gates, and different levels of athletes, performed against the laser gun or 3D motion capture system over multiple days. Of particular interest, which is lacking in the current study, would be the assessment of between-days minimum detectable change, where multiple sprints would be repeated on non-consecutive days. This work would provide more insight into the most valid, reliable, and sensitive method of estimating the acceleration-velocity profile of the short sprints.

In conclusion, given the results of this study, practitioners using timing gates to estimate short sprint acceleration-velocity profiles in general or maximum acceleration indices in particular should be wary of using the results in judging current state or performance improvement over time. Although maximum-sprinting speed indices demonstrated satisfactory agreement and sensitivity, if interested in measuring and tracking maximum acceleration indices, researchers and practitioners should be cautious when using timing gates and should probably invest in more precise and sensitive technology such as the laser gun.

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SUPPLEMENTARY DOCUMENTS

Ethic committee approval

УНИВЕРЗИТЕТ У БЕОГРАДУ
ФАКУЛТЕТ СПОРТА И ФИЗИЧКОГ ВАСПИТАЊА
02 Бр 877/23-2
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UNIVERZITET U BEOGRADU
FAKULTET SPORTA I FIZIČKOG VASPITANJA
ETIČKI KOMITET

Predmet - Na zahtev zaveden pod brojem 02-877/23-1 od 24. 14. 2023. godine, koji je podneo Mladen Jovanović, student doktorskih studija, Etički komitet Fakulteta sporta i fizičkog vaspitanja Univerziteta u Beogradu daje

S A G L A S N O S T

Za sprovođenje istraživanja pod naslovom „Effects of the flying start on estimated short sprint profiles using timing gates (Uticaj letećeg starta na procenu profila kratkih sprinteva primenom foto ćelija) za potrebe doktorske disertacije na Univerzitetu u Beogradu – Fakultetu sporta i fizičkog vaspitanja.

O b r a z l o ž e nj e

Na osnovu uvida u projekat istraživanja, Etički komitet Fakulteta iznosi mišljenje da se, kako u konceptu tako i u planiranju realizacije istraživanja i primene dobijenih rezultata, polazilo od principa koji su u skladu sa etičkim standardima, čime se obezbedjuje zaštita ispitanika od mogućih povreda njihove psiho-socijalne i fizičke dobrobiti.

U skladu sa iznetim mišljenjem Etički komitet Fakulteta daje saglasnost za realizaciju istraživanja „*Effects of the flying start on estimated short sprint profiles using timing gates (Uticaj letećeg starta na procenu profila kratkih sprinteva primenom foto ćelija)*".

U Beogradu, 8. 5. 2023.

Članovi

1. red. prof. dr Ana Orlić

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2. red. prof. dr Marina Đorđević-Nikić

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3. van. prof. dr Lidija Moskovljević

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eCollection 2021.

Sprint Mechanical Characteristics of Female Soccer Players: A Retrospective Pilot Study to Examine a Novel Approach for Correction of Timing Gate Starts

Jason D Vescovi [1], Mladen Jovanović [2]

Affiliations + expand

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Free PMC article

Abstract

The purpose of this study was to compare model estimates of linear sprint mechanical characteristics using timing gates with and without time correction. High-level female soccer players (n = 116) were evaluated on a 35-m linear sprint with splits at 5, 10, 20, 30, and 35 m. A mono-exponential function was used to model sprint mechanical metrics in three ways: without a time correction, with a fixed (+0.3 s) time correction, and with an estimated time correction. Separate repeated-measures ANOVAs compared the sprint parameter estimates between models and also the residuals between models. Differences were identified between all modeled sprint mechanical metrics; however, comparable estimates to the literature occurred when either time correction was used. Bias for both time-corrected models was reduced across all sprint distances compared to the uncorrected model. This study confirms that a time correction is warranted when using timing gates at the start line to model sprint mechanical metrics. However, determining whether fixed or estimated time corrections provide greater accuracy requires further investigation.

Keywords: force; maximum acceleration; maximum sprint speed; mono-exponential function; power.

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{shorts}: An R Package for Modeling Short Sprints

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Keywords: sprinting, speed, profiling, modeling, force-velocity profiling

Abstract

Short sprint performance is one of the most distinguishable and admired physical traits in sports. Short sprints have been modeled using the mono-exponential equation that involves two parameters: (1) maximum sprinting speed (MSS) and (2) relative acceleration (TAU). The most common methods to assess short sprint performance are with a radar gun or timing gates. In this paper, we: 1) provide the **shorts** package that can model sprint timing data from these two sources; 2) discuss potential issues with assessing sprint time (synchronization and flying start, respectively); and 3) provide model definitions within the **shorts** package to help alleviate errors within the subsequent parameter outcomes.

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Bias in estimated short sprint profiles using timing gates due to the flying start: simulation study and proposed solutions

Mladen Jovanović [1]

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PMID: 36708323 DOI: 10.1080/10255842.2023.2170713

Abstract

Short sprints are most frequently evaluated and modeled using timing gates. Flying start distance is often recommended to avoid premature timing system triggering by lifting knees or swinging arms. This results in timing system initiation not being aligned with the initial force application, which yields bias in estimated short sprint parameters. This simulation study aims to explore the effects of the flying start distance on bias and sensitivity to detect changes in short sprint parameters using three models: the contemporary No Correction model and two proposed Estimated time correction (Estimated TC), and Estimated flying distance (Estimated FD) models. In conclusion, both the Estimated TC and Estimated FD models provided more precise parameter estimates, but surprisingly, the No correction model provided higher sensitivity for specific parameter changes. Besides standardizing the sprint starting technique for the short sprint performance monitoring, practitioners are recommended to utilize and track the results of all three models.

Keywords: Acceleration; error; model; profile; velocity.

BIOGRAPHY

Born on the 17th of October 1982, in Šabac, Serbia. In 1990, he moved with his family to Pula, Croatia, where he finished the "OŠ Centar" elementary school. After finishing Technical High School as a computer technician in 2001, he moved to Belgrade, Serbia, to study strength and conditioning at the "Faculty of Sport and Physical Education" where he graduated as a professor of sport in 2007. Afterward, he worked as a strength and conditioning coach and sports scientist for Hammarby Football Club from Stockholm, Sweden, Aspire Academy from Doha, Qatar, and Port Adelaide Football Club from Adelaide, Australia. He started a successful website, www.complementarytraining.net, in 2010. In the 2016/17 school year, he enrolled in the doctoral program at the Faculty of Sport and Physical Education – University of Belgrade. He published three books: *HIIT Manual*, *Strength Training Manual,* and *bmbstats: Bootstrap Magnitude-based Statistics for Sports Scientists.*

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