Bias in estimated short sprint profiles using timing gates due to the flying start: simulation study and proposed solutions[1]

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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, profile, velocity, model

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Introduction

Sprint speed is one of the most distinctive and admired physical characteristics in sports. In most team sports (e.g., soccer, field hockey, handball, etc.), short sprints are defined as maximal sprinting from a standstill across a distance that does not result in deceleration at the finish. Peak anaerobic power is reached during the first few seconds (<5 s) of maximal efforts (Mangine et al. 2014); however, the capacity to attain maximal sprint speed is athlete- and sport-specific. For instance, track and field sprinters are trained to achieve maximal speed later in a race (i.e., 50-60 m) (Ward-Smith 2001), whereas team sport athletes have sport-specific attributes and reach maximal speed much earlier (i.e., 30-40 m) (Brown et al. 2004). The evaluation of short sprint performance is frequently included in a battery of fitness tests for various sports, regardless of the kinematic differences between athletes.

The use of force plates is regarded as the gold standard for analyzing the mechanical features of sprinting; nevertheless, collecting the profile of a whole sprint presents practical and cost problems (Samozino et al. 2016; Morin et al. 2019). Radar and laser technology are frequently utilized laboratory-grade methods (Buchheit et al. 2014; Jiménez-Reyes et al. 2018; Marcote-Pequeño et al. 2019; Edwards et al. 2020) that are typically unavailable to sports practitioners. Timing gates are unquestionably the most prevalent method available for modeling and evaluating sprint performance. Multiple gates are placed at different distances to capture split times (e.g., 10, 20, 30, and 40 m), which can now be incorporated into the method for determining sprint mechanical properties (Samozino et al. 2016; Morin et al. 2019). Practitioners can utilize the outcomes to explain individual differences, quantify the effects of training interventions, and gain a better knowledge of the limiting variables of performance.

To ensure accurate short sprint parameter estimates using timing gates, the initial force production must be synced with start time, often referred to as "first movement" triggering (Haugen et al. 2012; Haugen and Buchheit 2016; Samozino et al. 2016; Haugen et al. 2019; Haugen, Breitschädel, and Seiler 2020; Haugen, Breitschädel, and Samozino 2020). This represents a challenge when collecting sprint data using timing gates and can substantially impact estimated parameters. From a measurement perspective, *flying start* distance is often recommended to avoid premature triggering of the timing system by lifted knees or swinging arms (Altmann et al. 2015; Haugen and Buchheit 2016; Altmann et al. 2017; Altmann et al. 2018; Haugen, Breitschädel, and Samozino 2020). Flying start can also result from body rocking during the standing start. Clearly, any flying start with a difference between the initial force production and the start time can lead to bias in estimated short sprint parameters. Since it is hard to get faster at a sprint, inconsistent starts can hide the effects of the training intervention. This work aims to explore the bias and sensitivity to detect changes due to flying start involved when estimating short sprint parameters under simulated conditions. In addition, two novel model definitions are proposed with the aim of minimizing the parameter bias and increasing sensitivity to detect changes. This is needed to provide a theoretical understanding of the limits and expected errors of the short sprints modeling, which can later inform more practical studies involving athletes.

Methods

Mathematical model

The mono-exponential Equation 1 has been used to model short sprints. It was first proposed by Furusawa et al. (1927) and made more popular by Clark et al. (2017) and Samozino et al. (2016). Equation 1 is the function for instantaneous horizontal velocity

v given time t and two model parameters: (1) *Maximum sprinting speed* (MSS; expressed in ms^{-1}) and (2) *relative acceleration* (TAU; expressed in s).

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

TAU represents the ratio of MSS to initial acceleration (MAC; *maximal acceleration*, expressed in ms^{-2}) (Equation 2). Note that TAU, given Equation 1, can be interpreted as the time required to reach a velocity equal to 63.2% of MSS.

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

Although TAU is utilized in the equations and afterward estimated, it is preferable to use and report MAC because it is simpler to understand, especially for practitioners and coaches. By deriving Equation 1, Equation 3 is obtained for horizontal acceleration.

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

By integrating Equation 1, the equation for distance covered (Equation 4) is obtained.

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

Model parameters estimation using timing gates split times

Table 1 contains sample split times measured during 40 m sprint performance using timing gates positioned at 5, 10, 20, 30, and 40 m.

[Insert Table 1 here]

To estimate model parameters using split times, distance is a *predictor*, and time is the *outcome* variable; hence, Equation 4 takes the form of Equation 5 (Vescovi and Jovanović 2021; Jovanović and Vescovi 2022).

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

W in Equation 5 represents *Lambert's W* function, which is defined to be the multivalued inverse of the function $f(w) = we^{w}$ (Corless et al. 1996; Goerg 2022). Equation 4, in which time is the predictor and distance is the outcome variable, is commonly employed in research (Morin 2017; Morin and Samozino 2019; Stenroth and Vartiainen 2020). This method should be avoided since reversing the predictor and outcome variables in a regression model may create biased estimated parameters (Motulsky 2018, p. 341). This bias may not be practically significant for profiling short sprints, but it is a statistically flawed practice and should be avoided. It is thus preferable to utilize statistically correct Equation 5 to estimate model MSS and TAU. Estimating MSS and TAU parameters using Equation 5 as the model definition is performed using *non-linear least squares regression*. To the best of my knowledge, scientists, researchers, and coaches have been performing short sprints modeling using the built-in solver function of Microsoft Excel (Microsoft Corporation, Redmond, Washington, United States) (Samozino et al. 2016; Clark et al. 2017; Morin 2017; Morin et al. 2019; Stenroth et al. 2020; Stenroth and Vartiainen 2020). These, and additional functionalities, have been recently implemented in the open-source **{shorts}** package (Vescovi and Jovanović 2021; Jovanović 2022; Jovanović and Vescovi 2022) for R-language (R Core Team 2022), which utilizes the *nlsLM()* function from the **{minpack.lm}** package (Elzhov et al. 2022). Compared to the built-in solver function of Microsoft Excel, the **{shorts}** package represents a more feature-rich, flexible, transparent, and reproducible environment for modeling short sprints. It is used in this study to estimate model parameters.

Using the split times from Table 1, estimated MSS, TAU, and MAC parameters equal to 9.02 ms^{-1}, 1.14 s, and 7.94 ms^{-2}, respectively. *Maximal relative power* (PMAX;

expressed in W/kg) is an additional parameter often estimated and reported (Samozino et al. 2016; Morin et al. 2019). PMAX is calculated using Equation 6. This method of PMAX estimation disregards the air resistance and thus represents *net* or relative *propulsive* maximal power. Calculated PMAX using estimated MSS and MAC parameters equal to 17.91 W/kg.

$$PMAX = \frac{MSS \times MAC}{4} \qquad (6)$$

Problems with parameters estimation using split times due to flying start and reaction time

To demonstrate impact of the flying start and reaction time on estimated parameters, imagine three hypothetical triplet brothers, Mike, Phil, and John, with the same short sprint characteristics: MSS equal to 9 ms^{-1}, TAU equal to 1.125 s, MAC equal to 8 ms^{-2}, and PMAX equal to 18 W/kg (these represent *true* short sprint parameters). They all performed a 40 m sprint from a standing start using timing gates positioned at 5, 10, 20, 30, and 40 m. For Mike and Phil, the timing system is activated by the initial timing gate (i.e., when they cross the beam) at the start of the sprint (i.e., $d = 0\ m$). For John, the timing system is activated after the gunfire.

Mike represents the *theoretical model*, in which it is assumed that the initial force production and the timing initiation are perfectly synchronized. Mike's split have already been enlisted in Table 1. Phil decided to move slightly behind the initial timing gate (i.e., for 0.5 m) and used body rocking to initiate the sprint start. In other words, Phil used a *flying start*, a common scenario when testing field sports athletes. Since the gunfire triggers John's start, his split times have an additional reaction time of 0.2 s. This is similar to a scenario where the athlete prematurely triggers a timing system when standing too close to the initial timing gate. John's data can thus be used to demonstrate the effects of this scenario on the estimated parameters.

Timing gates utilized in this theoretical example provide precision to two decimals (i.e., closest 10 ms), representing a measurement error source. A graphical representation of the sprint splits can be found in Figure 1.

[Insert Figure 1 here]

Estimated sprint parameters can be found in Table 2. As seen from the results (Table 2), estimated short sprint parameters for all three brothers differ from the *true* parameters used to generate the data (i.e., their *true* short sprint characteristics). All three brothers have a bias in estimated parameters due to timing gates' precision to 2 decimals (i.e., 10 ms). Bias in estimated parameters in Phil's case is due to the flying start involved, while in John's case, it is due to the reaction time involved in the split times.

[Insert Table 2 here]

How to overcome missing the initial force production when using timing gates?

The literature suggests using a correction factor of +0.5 s as a viable solution (i.e., simply adding +0.5 s to split times) to convert to "first movement" triggering when utilizing recommended 0.5 m flying distance behind the initial timing gate (Haugen et al. 2012; Haugen and Buchheit 2016; Haugen et al. 2019; Haugen, Breitschädel, and Seiler 2020). Intriguingly, the average difference between the standing start with a photocell trigger and a block start to gunfire for a 40-meter sprint was 0.27 s (Haugen et al. 2012). Consequently, although a timing correction factor is required to prevent further inaccuracies in estimates of kinetic variables (e.g., overestimate power), a correction factor that is too big would have the opposite effect (e.g., underestimate power).

The Estimated time correction model

Instead of using *apriori* time correction from the literature, this parameter may be estimated using the supplied data, together with MSS and TAU. Stenroth et al. (2020) propose the same approach, titled the *time shift method*, and the estimated parameter, named the *time shift parameter*. In accordance with the current literature, this parameter is termed *time correction* (TC) (Vescovi and Jovanović 2021).

Using the original Equation 5 to implement the TC parameter now yields the new Equation 7. Equation 7 is utilized as the model definition in the *Estimated TC* model, as opposed to the model using Equation 5, which is termed the *No correction* model in this study. The model in which TC is fixed (i.e., by simply adding TC to split times) is termed the *Fixed TC* model.

$$t(d) = TAU \times W\left(-e^{\frac{-d}{MSS \times TAU}} - 1\right) + \frac{d}{MSS} + TAU - TC \qquad (7)$$

From a regression perspective, the TC parameter can be viewed as an *intercept*. It can be beneficial when assuming a fixed time shift is involved (i.e., reaction time or premature triggering of the timing equipment). Comparing the split times of Mike and John in Figure 1, it can be noticed that the lines are parallel. In this scenario, the *Estimated TC* model can remove bias between Mike and John. The *Estimated TC* model can also help remove bias in estimated parameters in Phil's case. However, when looking closely at Figure 1, it can be noticed that Phil's and Mike's lines are not parallel. This is because there is already some velocity when the initial timing gate is triggered; thus, the time shift is not constant.

These models (i.e., *Fixed TC* of +0.3, +0.5 s, and *Estimated TC* model) are applied to Mike, Phil, and John's split times. The estimated model parameters can be found in Table 3, and previously estimated parameter values using the *No correction* model. As can be noted from Table 3, adding +0.3 s worked well for Phil in terms of approaching *true* parameter values, while adding +0.5 s was detrimental in un-biasing estimated parameters. The *Estimated TC* model worked well for all three athletes in terms of un-biasing the parameter estimates. The estimated TC parameter for John was also very close to the *true* reaction time of 0.2 s.

Estimated flying distance model

Although the *Estimated TC* model performed well in Phil's case (triplet brother doing flying start), instead of assuming time shift (which helps in un-biasing the estimates compared to the *No correction* model), the model definition that assumes *flying start distance* (FD) involved in the *data-generating-process* (DGP) can be utilized. This *Estimated FD* model utilizes Equation 8 as the model definition.

$$\begin{aligned} t(d) \quad &= \left(TAU \times W\left(-e^{\frac{-d+FD}{MSS \times TAU}} - 1\right) + \frac{d+FD}{MSS} + TAU\right) \\ &\quad - \left(TAU \times W\left(-e^{\frac{FD}{MSS \times TAU}} - 1\right) + \frac{FD}{MSS} + TAU\right) \end{aligned} \qquad (8)$$

Table 3 contains all model estimates for three brothers, including the *Estimated FD* model. It can be noticed that the *Estimated FD* model unbiased estimates for Phil but failed to be estimated for John (brother that starts at gunfire and has reaction time involved in his split times). This is because the *Estimated FD* model is *ill-defined* under that scenario and cannot have a *negative* flying distance.

Overall, each model definition has assumed the mechanism of the data generation. *No correction* model assumes perfect synchronization of the sprint initiation with the start of the timing. The *Estimated TC* model introduces a simple intercept that can help estimate parameters when an assumed time shift is involved (e.g., when reaction time is involved or premature triggering of the initial timing gate). *Estimated TC* can also be used when flying start is utilized, but it assumes the constant time shift, which is not the case in that scenario due to already gained velocity at the start. The *Estimated FD* model assumes there is a flying sprint involved in the DGP and, as shown in Table 3, can be ill-defined when there is no flying distance involved but there is a time shift. All three models assume athlete accelerates according to the mono-exponential Equation 1.

[Insert Table 3 here]

Simulation design

To explore the behavior of these three models under simulated and known conditions, short sprints data is generated using *true* MSS (ranging from 7 to 11 $ms^{-}1$, in increments of 0.05 $ms^{-}1$, resulting in a total of 81 unique values), MAC (ranging from 7 to 11 $ms^{-}2$, in increments of 0.05 $ms^{-}2$, resulting in a total of 81 unique values), and flying distance (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 consisted of 6,561 MSS and MAC combinations. Split times are estimated using timing gates positioned at 5, 10, 20, 30, and 40 m, with the rounding to the closest 10 ms. In total, there were 334,611 sprints simulated.

Statistical analysis

MSS, MAC, TAU, and PMAX are estimated for each simulated sprint using the *No correction*, *Estimated TC*, and *Estimated FD models*. The agreement between *true* and estimated parameter values is evaluated using the *percent difference* ($\%Diff$) estimator (Equation 9).

$$\%Diff = 100 \times \frac{estimated - true}{true} \qquad (9)$$

The distribution of the simulated $\%Diff$ is summarized using $median$ and 95% *highest-density continuous interval* ($HDCI$) (Kruschke 2015; Kruschke and Liddell 2018a; Kruschke and Liddell 2018b; Kruschke 2018; Makowski et al. 2019). To provide magnitude interpretation of the $\%Diff$, *region of practical equivalence* ($ROPE$), as well as the proportion of the simulations that lie within $ROPE$ ($inside\ ROPE$; expressed as a percentage) (Kruschke 2015; Kruschke and Liddell 2018a; Kruschke and Liddell 2018b; Kruschke 2018; Makowski et al. 2019; Jovanović 2020), are calculated. $ROPE$ is assumed to be equal to 95% $HDCI$ of the $\%Diff$ using the *No correction* model and no flying distance. Theoretically, $ROPE$ represents the lowest error (i.e., the best agreement) that can be achieved. It is limited purely by the timing gates' measurement precision (i.e., rounding to the closest 10 *ms*) and simulated parameters.

In addition to estimating agreement between *true* and estimated parameter values, practitioners are often interested in whether they can use estimated values to track changes in the *true* parameter values. A *minimal detectable change* estimator with 95% confidence ($\%MDC_{95}$) (Furlan and Sterr 2018; Jovanović 2020) is 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. $\%MDC_{95}$ is calculated using *percent residual standard error* ($\%RSE$; Equation 10) of the linear regression between *true* (predictor) and estimated parameter values (outcome) (Equation 11). Since simulated data with the known *true* values are utilized, $\%RSE$ represents the *percent standard error of the measurement* ($\%SEM$) in the estimated parameters.

$$\%RSE = \sqrt{\frac{\sum_{i=1}^{N}\left(100 \times \frac{y_i - \widehat{y}_i}{\widehat{y}_i}\right)^2}{N-2}} \qquad (10)$$

$$\%MDC_{95} = \%RSE \times \sqrt{2} \times 1.96 \qquad (11)$$

In addition to providing $\%MDC_{95}$ for the estimated parameters, the lowest $\%MDC_{95}$ is 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 are performed on both *pooled* dataset (i.e., using all flying distances) and across every flying distance. It is hypothesized that the *Estimated FD* model will have the highest $inside\ ROPE$ estimates and the lowest $\%MDC_{95}$ estimates. Statistical analyses and graph construction were performed using the software R 4.2.1 (R Core Team 2022) in RStudio (version 2022.07.1+554).

Results

Model fitting

Table 4 contains failed model fitting for the *Estimated FD* model. These were disregarded from further analysis. The reason for these failed model fittings is probably the combination of the very small flying distance and the measurement precision of the timing gates, resulting in an ill-defined model that cannot be fitted.

[Insert Table 4 here]

Percent difference

Region of practical equivalence

Estimated ROPEs are equal to -0.3 to 0.33% for MSS, -0.73 to 0.74% for MAC, -1.03 to 1% for TAU, and -0.5 to 0.5% for PMAX (Table 5) and are depicted as grey horizontal bars in Figure 2 and Figure 3.

Pooled analysis

The pooled analysis is performed using all flying distances pooled together. As such, the pooled analysis represents the overall estimate of the agreement between *true* and estimated parameter values across simulated conditions. Figure 2 depicts the distribution of the pooled $\%Diff$ estimator. Table 5 contains the pooled analysis results summary for every model and short sprint parameter.

[Insert Figure 2 here]

[Insert Table 5 here]

Analysis across flying distances

Figure 3 depicts the analysis results for every flying distance in the simulation. $Inside\ ROPE$ parameter estimates are calculated and depicted in Figure 4 for easier comprehension.

[Insert Figure 3 here]

[Insert Figure 4 here]

Minimal detectable change

Lowest Minimum Detectable Change

Estimated $\%MDCs_{95}^{lowest}$ is equal to 0.45% for MSS, 1.06% for MAC, 1.47% for TAU, and 0.7% for PMAX (column *lowest* in Table 6) and dashed grey horizontal lines in Figure 5.

Pooled analysis

Estimated parameters' $\%MDCs_{95}$ for the *No correction* model range from 3 to 44%, for the *Estimated TC* range from 1 to 8%, and for the *Estimated FD* range from 1 to 7% (Table 6).

[Insert Table 6 here]

Analysis across flying distances

The estimated $\%MDCs_{95}$ across flying distances are depicted in Figure 5. For every short sprint parameter, *Estimated TC* showed stable and lower $\%MDCs_{95}$ compared to *Estimated FD* (from 1 to 6% and from 1 to 8%, respectively). The *No correction* model showed the lowest $\%MDCs_{95}$ for the MAC and TAU parameters, ranging from 1 to 5% and from 1 to 3%, respectively.

[Insert Figure 5 here]

Discussion

The aim of this study was to estimate the agreement between *true* short sprint parameter values and *estimated* parameter values using three model definitions under simulated conditions. This agreement is estimated using the $\%\boldsymbol{Diff}$ estimator (Equation 9). In addition to estimating agreement, this study aims to estimate the sensitivity of the models to detect changes in *true* short sprint parameter values. This sensitivity is estimated using the $\%\boldsymbol{MDC_{95}}$ estimator (Equation 11). Agreement and sensitivity analysis is performed using the *pooled* dataset and across simulated flying sprint distances.

Agreement between true and estimated short sprint parameters

Region of practical equivalence

An interesting finding is that, given simulation parameters (particularly the precision of the timing gates to the closest 10 ms), MSS has the lowest $ROPE$ compared to other short sprint parameters (Table 5 and Figure 2). Since $ROPE$ represents the lowest estimation error, MSS is the parameter that could be, given this theoretical simulation, estimated with the most precision. In contrast, TAU and MAC can be estimated with the least precision.

Pooled analysis

As expected, the *Estimated FD* model performed with the highest $inside\ ROPE$ parameter values (from 20 to 72%), with the narrowest 95% $HDCI$s (from -5 to 5%), and no bias involved (Table 5 and Figure 2). On the other hand, the *No correction* model performed poorly, with the lowest inside $ROPE$ parameter values (from 2 to 2%), with the widest 95% $HDCI$s (from -46 to 80%), and with the apparent bias indicated with the $median$ parameter values being outside of $ROPE$ (from -35 to 49%) (Table 5 and Figure 2). In addition, a visual inspection of Figure 2 indicates a *non-normal* distribution of estimated $\%Diff$ parameter values, demanding further analysis across flying distance values. The *Estimated TC* model performed similarly to the *Estimated FD* model with a slightly lower $inside\ ROPE$ parameter values (from 9 to 67%), wider 95% $HDCI$s (from -9 to 8%), and with obvious bias, although much smaller than the *No correction* model bias (from -3 to 3%) (Table 5 and Figure 2).

Analysis across flying distances

As expected, the *No correction* model demonstrated increasing bias as the flying distance increased (from -46 to 76%), the widest 95% $HDCI$s (from -47 to 84%), and the lowest $inside\ ROPE$ estimated parameter values (Figures 3 and 4). *Estimated TC* showed a small bias trend across flying distances (from -6 to 6%), resulting in decreasing $inside\ ROPE$ performance (from 0 to 75%; see Figure 4), although with much smaller 95% $HDCI$s (from -10 to 11%) compared to *No correction* model. *Estimated FD,* as hypothesized, showed no bias and thus a stable $inside\ ROPE$ performance across flying distances (see Figure 4), with minimal 95% $HDCI$s (from -5 to 6%).

Sensitivity to detect changes in true short sprint parameters

Lowest Minimum Detectable Change

An interesting finding is that, given simulation parameters (particularly the precision of the timing gates to the closest 10 ms), MSS has the lowest $\%MDCs_{95}^{lowest}$ compared to other short sprint parameters (Table 6). Since $\%MDCs_{95}^{lowest}$ represents the lowest minimal detectable change, MSS is the parameter whose change could be, given this theoretical simulation, estimated with the most precision. In contrast, TAU and MAC changes can be estimated with the least precision.

Pooled analysis

Pooled $\%MDCs_{95}$ represents an estimate of the *sensitivity* to detect *true* change with 95% confidence when the flying start distance is not standardized (but within simulation parameter limits (ranging from 0 to 0.5 m). As expected, the *No correction* model demonstrates the highest $\%MDCs_{95}$ (from 3 to 44%), while *Estimated TC* and *Estimated FD* demonstrated much smaller $\%MDCs_{95}$ (from 1 to 8% and from 1 to 7%, respectively) (Table 6).

An interesting finding is that the MSS parameter showed very low $\%MDCs_{95}$ across models (from 1 to 3%), even for the *No correction* model. This indicates that even the non-standardized short sprint monitoring (i.e., without standardized flying distance) using the *No correction* model, given simulation parameters, can be used to track changes in MSS. TAU, MAC, and PMAX parameters, on the other hand, demand a much larger $\%MDCs_{95}$ (from 7 to 44%, from 6 to 37%, and from 6 to 36%, respectively).

Analysis across flying distances

When estimated across flying distances, $\%MDCs_{95}$ shows interesting and surprising patterns (Figure 5). For every short sprint parameter, *Estimated TC* showed stable and lower $\%MDCs_{95}$ compared to *Estimated FD* (from 1 to 6% and from 1 to 8%, respectively). This is surprising because even if it demonstrated biased estimates of short sprint parameters (Figures 3 and 4) compared to the *Estimated FD*, *Estimated TC* might be more sensitive to detect *changes*, given simulation parameters.

Another surprising finding is that the *No correction* model, even if shown to be highly biased in estimating short sprint parameter values (Figures 3 and 4), showed the lowest $\%MDCs_{95}$ for the MAC and TAU parameters (from 1 to 5% and from 1 to 3% respectively). This indicates that when short sprint measurement is standardized (i.e., athletes perform with the same flying distance), given the simulation parameters, the *No correction* model can be the most sensitive model to detect *changes* in MAC and TAU parameters. This is unfortunately not the case for the MSS and PMAX parameters (from 0 to 3% and from 1 to 9%, respectively) (Figure 5).

Overall, when it comes to estimating *changes* in short sprint parameters, *change* in MSS is the most sensitive to be detected (from 0 to 3%) compared to MAC (from 1 to 7%), TAU (from 1 to 8%), and PMAX (from 1 to 9%) (Figure 5).

Conclusions

The simulation study employed demonstrated some expected and unexpected theoretical findings. Among the expected findings are (1) the bias and low $inside\ ROPE$ performance in estimating short sprint parameters using the *No correction* model, (2) more negligible bias and higher $inside\ ROPE$ for the *Estimated TC* model, and (3) no bias and highest $inside\ ROPE$ for the *Estimated FD* model. The unexpected finding of this study is the performance of the *No correction* model in sensitivity of estimating the *change* of the MAC and TAU parameters, which outperformed the other two models.

When estimating short sprint parameters across models, given simulation parameters, MSS and *change* in MSS can be estimated more precisely compared to TAU, MAC, and PMAX parameters and their *changes*.

In addition to model performances, this simulation study provided the theoretical $ROPE$s and $\%MDCs_{95}^{lowest}$ estimates. These could be useful for further validity and reliability studies evaluating short sprint model performance involving *real* athletes by providing minimal theoretical values one can achieve with timing gates positioned at the exact distances with the exact time rounding.

The takeaway message for the practitioners is that besides standardizing the sprint starting technique for the short sprint performance monitoring, it would be wise to utilize and track the results of all three models. The *Estimated FD* model will provide unbiased estimates of the current performance, but the *No correction* model might be more sensitive in detecting changes in TAU and MAC parameters.

This practical conclusion should be taken with caution since it is based on the results of this theoretical simulation. Additional studies involving *real* athletes in evaluating the performance of these three models are needed. These studies should involve estimating the short sprint parameters agreement between gold-standard (i.e., *criterion*) measure (e.g., radar gun, laser gun, or video analysis) and *practical* measure using timing gates with different timing initiation (e.g., crossing the beam, foot pressing on force sensor or leaving the ground) under different flying start conditions and distances (e.g., start on the line, start at 0.5 m behind the initial timing gate, use of body-rocking) to practically demonstrate bias introduced when timing initiation is not synchronizes with initial force application. In addition to theoretical findings, such studies will provide model performance estimates when biological variability is involved in short sprints, which is not considered in the current study. One such study is currently in preparation.

Data availability statement

The data that support the findings of this study are openly available in the GitHub repository at https://github.com/mladenjovanovic/shorts-simulation-paper (DOI: 10.5281/zenodo.7094284), as well as the reproducible *Quarto* (Allaire et al. 2022) source code.

Declaration of interest statement

The author report there are no competing interests to declare

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Table 1: Sample split times measured during 40 m sprint performance using timing gates positioned at 5, 10, 20, 30, and 40 m.

Distance (m)	Split time (s)
5	1.34
10	2.06
20	3.29
30	4.44
40	5.56

Table 2: Estimated sprint parameters for Mike, Phil, and John. All three brothers have identical sprint performance but utilize different sprint starts, which results in different split times, and thus different sprint parameter estimates. Due to the timing gates' precision to 2 decimals (i.e., 10 ms), estimated Mike's parameters also differ from the *true* values.

Athlete	**MSS**	**TAU**	**MAC**	**PMAX**
True	*9.00*	*1.12*	*8.00*	*18.0*
Mike (theoretical)	9.02	1.14	7.94	17.9
Phil (flying start)	8.60	0.61	14.00	30.1
John (gunfire)	9.59	1.62	5.93	14.2

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)

Table 3: Estimated sprint parameters for Mike, Phil, and John for (1) *No correction*, (2) *Fixed time corrections* (Fixed TC) with +0.3s and +0.5s corrections, (3) *Estimated time correction* (Estimated TC), and (4) *Estimated flying start distance* (Estimated FD) models.

Model	**Athlete**	**MSS**	**TAU**	**MAC**	**PMAX**	**TC**	**FD**
	True	*9.00*	*1.12*	*8.00*	*18.0*		
No correction	Mike (theoretical)	9.02	1.14	7.94	17.9		
	Phil (flying start)	8.60	0.61	14.00	30.1		
	John (gunfire)	9.59	1.62	5.93	14.2		
Fixed +0.3s TC	Mike (theoretical)	10.01	1.93	5.19	13.0		
	Phil (flying start)	9.05	1.13	8.02	18.2		
	John (gunfire)	11.29	2.79	4.05	11.4		
Fixed +0.5s TC	Mike (theoretical)	11.29	2.79	4.05	11.4		
	Phil (flying start)	9.62	1.61	5.98	14.4		
	John (gunfire)	13.67	4.26	3.21	11.0		
Estimated TC	Mike (theoretical)	9.04	1.15	7.86	17.8	0.01	
	Phil (flying start)	9.00	1.08	8.35	18.8	0.28	
	John (gunfire)	9.04	1.15	7.86	17.8	-0.19	
Estimated FD	Mike (theoretical)	9.04	1.15	7.86	17.8		0.00
	Phil (flying start)	9.03	1.16	7.82	17.7		0.54
	John (gunfire)[a]						

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); TC – time correction (expressed in second); FD – flying start distance (expressed in meters)

[a] Failed to be estimated due to the ill-defined model for the time-reaction scenario

Table 4: Failed model fittings for 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

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.

Parameter	**ROPE (%)**	**Model**	**% Diff**	**Inside ROPE (%)**
MSS	-0.3 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%	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	-0.5 to 0.5%	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%

Note. MSS – maximum sprinting speed; TAU – relative acceleration; MAC – maximum acceleration; PMAX – maximal relative power HDCI - highest-density continuous interval

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.

Parameter	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	0.7 %	36 %	7 %	6 %

Note. MSS – maximum sprinting speed; TAU – relative acceleration; MAC – maximum acceleration; PMAX – maximal relative power

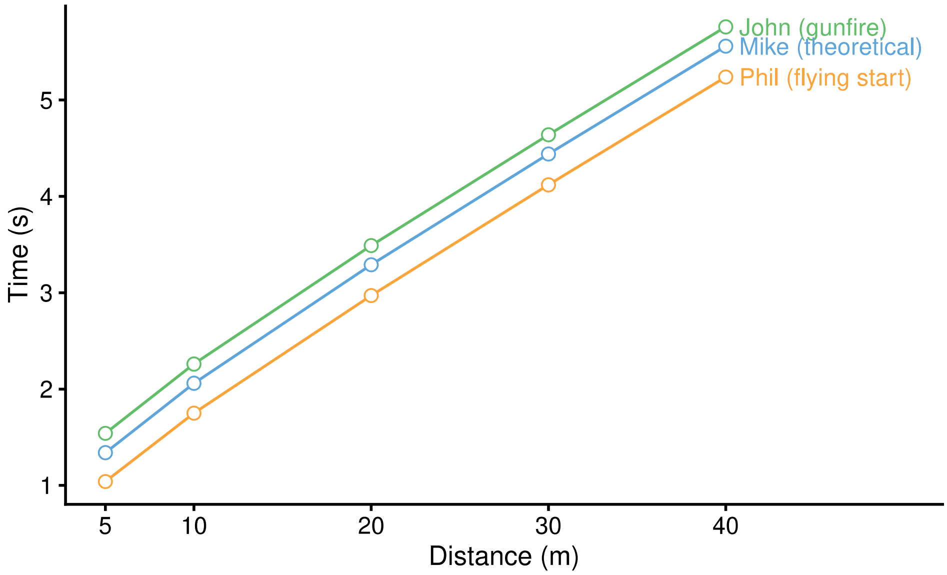

Figure 1: Phil, Mike, and John split times over a 40 m distance. All three brothers have identical sprint performances but utilize different sprint starts, resulting in different split times.

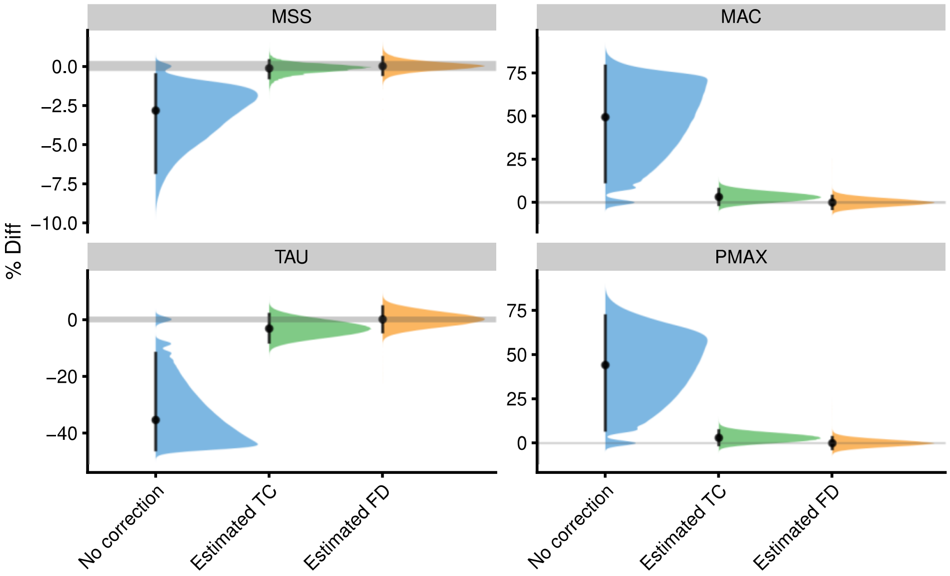

Figure 2: Pooled distribution of the percent difference ($\%Diff$) for (1) *No correction*, (2) *Estimated time correction* (Estimated TC), and (3) *Estimated flying start distance* (Estimated FD) models. Error bars represent the distribution $median$ and 95% highest-density continuous interval ($95\%\ HDCI$). 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; TAU – relative acceleration; MAC – maximum acceleration; PMAX – maximal relative power

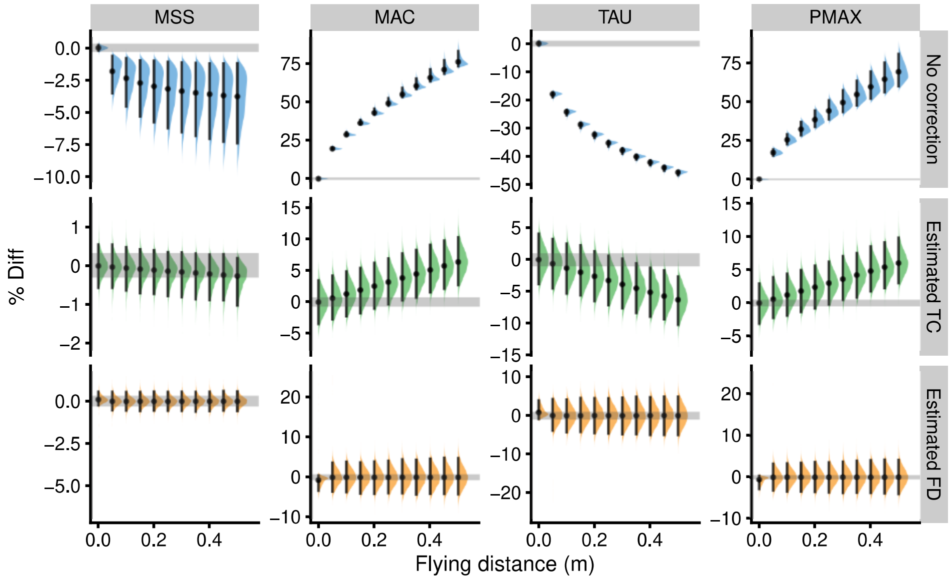

Figure 3: Distribution of the percent difference ($\%Diff$) across every flying distance in the simulation for (1) *No correction*, (2) *Estimated time correction* (Estimated TC), and (3) *Estimated flying start distance* (Estimated FD) models. Error bars represent the distribution $median$ and 95% highest-density 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; TAU – relative acceleration; MAC – maximum acceleration; PMAX – maximal relative power

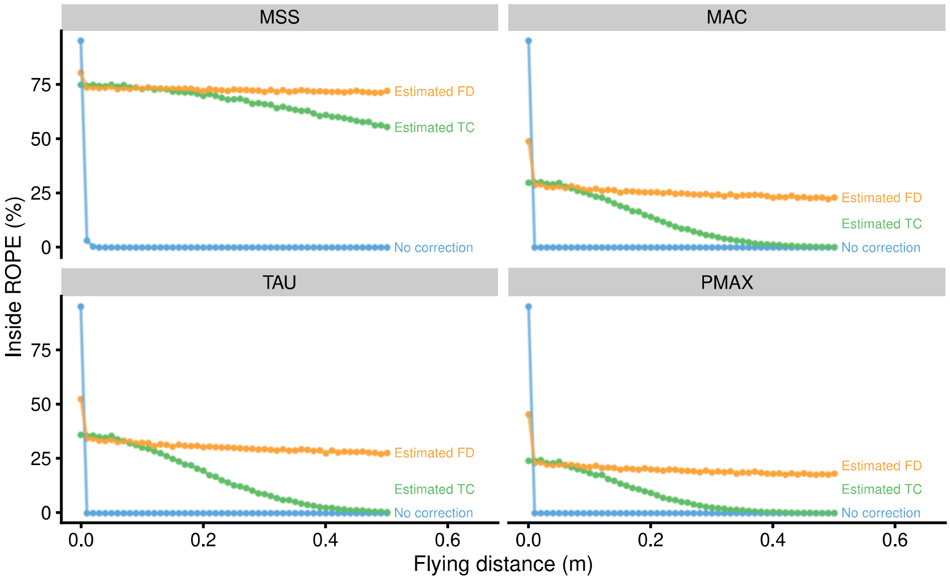

Figure 4: Percentage of the simulations that lie within the region of practical equivalence (*inside ROPE*) estimated across every flying distance in the simulation for (1) *No correction*, (2) *Estimated time correction* (Estimated TC), and (3) *Estimated flying start distance* (Estimated FD) models.

Note. MSS – maximum sprinting speed; TAU – relative acceleration; MAC – maximum acceleration; PMAX – maximal relative power

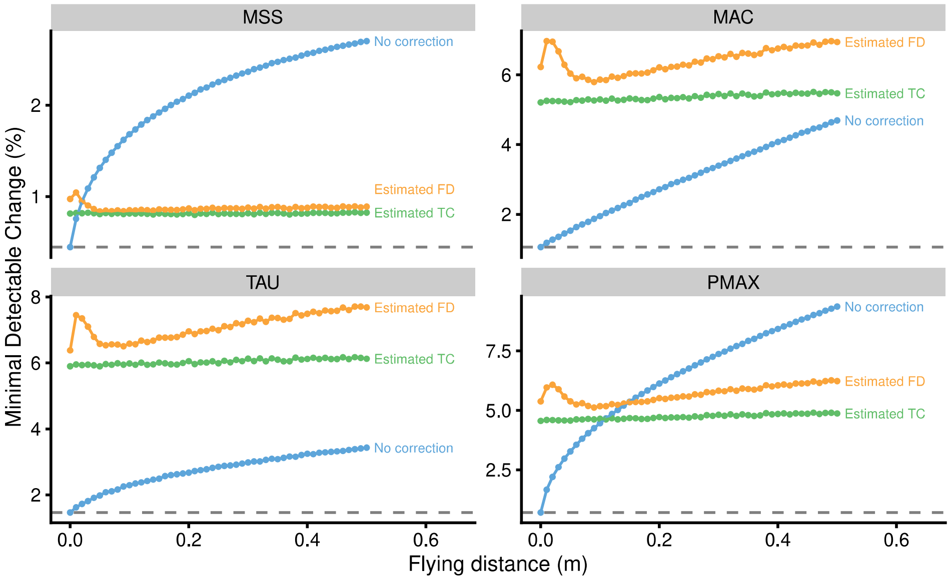

Figure 5: Estimated minimal detectable change using 95% confidence level ($\%MDCs_{95}$) across every flying distance in the simulation for (1) *No correction*, (2) *Estimated time correction* (Estimated TC), and (3) *Estimated flying start distance* (Estimated FD) models. The dashed line represents the lowest $\%MDCs_{95}$ estimated using the *No correction* model and no flying distance ($\%MDCs_{95}^{lowest}$).

Note. MSS – maximum sprinting speed; TAU – relative acceleration; MAC – maximum acceleration; PMAX – maximal relative power