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Let's get real: A framework for predicting intra-stride treadmill speed variations and for quantifying their effects on gait dynamics through simulation

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Let's get real: A framework for predicting intra-stride treadmill speed variations and for quantifying their effects on gait dynamics through simulation

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Abstract

Background: During treadmill walking, the treadmill belt speed is not constant but changes continuously throughout the stride as a result of the mechanical interaction between the participant and the treadmill. Typically, belt speed decreases shortly after heel strike, slightly overshoots during stance, and decreases again around toe-off. These deviations have been measured, but their dynamics and potential effects on human gait are insufficiently understood. In this work, we propose and validate a model that predicts instantaneous belt speed throughout the stride from ground reaction force data. We integrate this model into optimal control simulations of walking at different speeds to determine the impact of intra-stride belt speed deviations on various gait parameters. Finally, we use the simulations to explain the extent to which fluctuating belt speed contributes to reported differences between overground and treadmill gait.
Results: Our model can predict participant- and speed-specific belt-speed patterns with high accuracy. By integrating the model into optimal control simulations of walking at different speeds, we find that realistic belt-speed variations have negligible effects on joint angles, muscle activations, and energetics, while differences in joint moments occur mainly during loading response. Several simulated changes were consistent in direction with experimentally reported treadmill-overground differences, but their magnitude was small.
Conclusions: We introduced a new computational model that accurately predicts treadmill belt-speed deviations throughout the entire stride from GRF data, extending previous work that primarily measured these variations. The model further indicates that belt-speed variations depend primarily on the rate of change in GRF rather than GRF magnitude or participant body weight, as previously suggested. Our simulations showed that these intra-stride belt-speed variations generally need not be accounted for in gait simulations of normal walking under comparable treadmill conditions, except when joint moments during loading response are of particular interest. Finally, although several simulated changes were consistent with observed treadmill-overground differences, their overall small magnitude suggests that belt-speed variations play only a minor role in these differences. Our work therefore provides a tool to estimate belt-speed variations when direct measurements are unavailable and evidence to guide the choice of treadmill models in future gait simulations.

Keywords: treadmill, belt-speed variations, optimal control, gait analysis, gait simulations

1 Background

Treadmills are widely used tools in exercise, rehabilitation, and research. Compared to overground walking, they allow the continuous acquisition of gait within a small laboratory space while enabling synchronized use of stationary measurement equipment

[1, 2]. In addition, walking speed can be controlled, improving comparability across participants and sessions [3].

Prior research has shown that several aspects of treadmill walking differ from overground walking, despite the locomotor task being the same. A recent meta-analysis of 55 studies reported increased relative energy consumption during treadmill walking, as well as reduced peak knee extension and ankle dorsiflexion moments [4]. Kinematic measures, on the other hand, were generally found to be comparable between treadmill and overground walking [4].

Multiple factors contribute to the observed differences, like an altered visual environment, moving ground, or psychological factors [1, 2, 5]. Another contributor, and the focus of this work, are intra-stride belt speed variations. Rather than remaining constant, the treadmill belt velocity fluctuates throughout the gait cycle [2, 3, 6–8], resulting in energy transfer between human and belt [6]. These fluctuations arise from the interaction between the continuous, time-varying forces exerted by the walker on the belts and the treadmill control system, which updates belt speed at a finite sampling rate [2, 6]. The belt speed variations are gait-phase dependent, with the largest speed decrease occurring shortly after heel strike. Both the magnitude of this decrease and the overall belt speed variation depend on participant mass and walking speed [2]. Additionally, belt speed variations differ across treadmill types and modes [8, 9].

In human experiments, the contribution of treadmill belt-speed variations to gait is difficult to quantify due to the many other confounding factors distinguishing treadmill from overground walking. Therefore, the extent to which treadmill belt-speed variations contribute to the observed treadmill-overground walking differences remains insufficiently understood. Musculoskeletal simulations could overcome this as they allow individual system components to be manipulated independently to quantify their effects on human gait [10]. Realistic simulations of treadmill walking, however, require

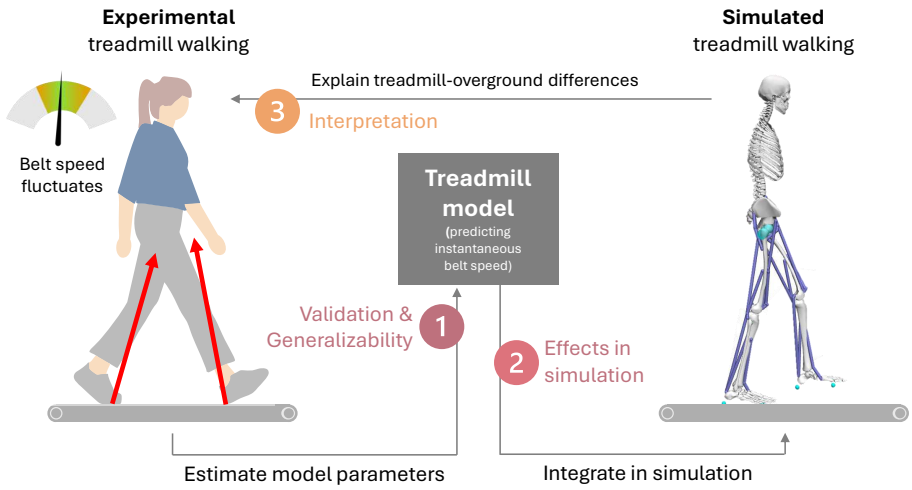

Fig. 1 Overview of the study goals and workflow. Experimentally recorded ground reaction force and treadmill speed data were used to fit the treadmill model parameters, and to test the validity and generalizability of the model (1). The validated treadmill model was subsequently integrated into optimal control simulations to assess the effects of realistic treadmill behaviour on simulated outcomes compared to an ideal treadmill representation (2). Finally, the simulation results were used to investigate the extent to which treadmill dynamics can explain experimentally observed differences between treadmill and overground walking in humans (3).

a model capable of predicting the instantaneous belt-speed fluctuations arising from the interaction between the participant and the treadmill.

Although belt-speed variations have been characterized experimentally, existing studies have largely focused on their measurement and group-level characterization [7–9], rather than on developing predictive models of their underlying dynamics. Without direct experimental speed measurements, it remains unclear how belt-speed trajectories evolve throughout the stride and how they vary across multiple participants with different walking patterns. Furthermore, a predictive model should be able to estimate how belt-speed fluctuations change when a participant's gait pattern is altered. To date, it has only been shown that certain gait features change in response to differences in the magnitude of belt-speed variations [6], but not how changes in gait affect belt-speed variations. Such a predictive model of belt-speed dynamics would

enable the incorporation of realistic treadmill dynamics into predictive biomechanical simulations of walking.

Generally, in most simulation studies and frameworks, treadmill walking is assumed to be biomechanically equivalent to overground walking, and treadmill-specific belt-speed variations are therefore typically neglected [11–15]. The only simulation study to use a non-ideal treadmill model was conducted by Jung et al. [16], who used a torque-driven model and found small kinematic changes when a gait controller trained for overground walking was applied to a non-ideal treadmill. However, their treadmill model was not validated against experimentally measured data, and the simulations did not account for the possibility that humans adapt their gait in response to the energetic interaction with the treadmill. Consequently, it remains unclear how realistic treadmill dynamics influence adapted gait mechanics, kinetics, muscle activations, and energetics.

The goals of this work are threefold (Figure 1). First, we develop a predictive treadmill model that estimates instantaneous belt-speed variations from the interaction forces between the walker and the treadmill, and evaluate its generalizability across participants and walking conditions based on experimental data. Second, we integrate this model into optimal control simulations of walking to quantify the effects of intra-stride belt-speed fluctuations on biomechanical variables. Third, we assess whether the simulated effects are consistent with differences reported between experimental treadmill and overground walking, thereby evaluating the extent to which belt-speed variations contribute to these observed changes.

2 Methdods

2.1 Realistic treadmill model

The realistic treadmill model predicts the instantaneous belt speed v at normalized stride index $n+1$ and is applied independently to each belt if multiple belts are present.

In the absence of foot-belt contact, belt speed is set to the nominal speed v_{nom}., as belt-speed fluctuations cannot influence gait without contact between the participant and the treadmill. During contact phases, v is computed as a function of the change rate of the anterior-posterior (AP) and vertical components of the ground reaction force (GRF), and a proportional-derivative (PD) controller:

$$v_{n+1} = v_n + K_{F_x}\dot{F}_{x,n-d} + K_{F_y}\dot{F}_{y,n-d} + K_P e_{n-1} + K_D \dot{e}_{n-2}, \tag{1}$$

where $n = 1...N$ denotes the normalized stride index with N being the total number of samples, $F_{x,n}$ and $F_{y,n}$ are the AP and vertical GRFs and $\dot{F}_{x,n}$ and $\dot{F}_{y,n}$ their time derivatives. K_{F_x}, K_{F_y}, K_P, and K_D are gain factors, d is a delay in discrete time steps, and e is the error between the actual and nominal belt speed defined as

$$e_n = v_{nom} - v_n. \tag{2}$$

The first two terms following v_n represent belt-speed changes caused by the forces exerted by the participant on the treadmill, whereas the latter two terms model the effect of the treadmill controller regulating belt speed toward the nominal value. This approach simplifies the problem, as accurately modelling the treadmill system requires knowledge of inertial and motor properties, control frequency, and other dynamics, which are often inaccessible.

The discrete time derivative of any signal s was approximated as

$$\dot{s}_n = \frac{s_{n+1} - s_n}{\Delta t}, \tag{3}$$

where $\Delta t = T/N$ is the time interval between consecutive stride-normalized samples computed from the stride duration T and the number of samples N. The delay d in

samples is computed from the time delay t_d in seconds as:

$$d = \text{round}\left(\frac{t_d}{\Delta t}\right). \tag{4}$$

K_{F_x}, K_{F_y}, K_P, K_D, and t_d are free model parameters which are determined via optimization using experimentally collected data.

2.2 Experimental data

We collected GRF and belt-speed data from 15 participants (74.4 ± 14.8 kg) walking on an instrumented dual-belt treadmill (GRAIL, Motek, the Netherlands) at five speeds (1.0, 1.2, 1.4, 1.6, and 1.8 m/s) for 190 s each. GRFs were recorded at 1000 Hz, while belt speed was obtained from the treadmill's internal velocity measurements at approximately 300 Hz. The study was approved by the ethics committee of Friedrich-Alexander-Universität Erlangen-Nürnberg (Re.-No. 22-437-B), with written informed consent from all participants. The first 10 s of each recording were discarded to exclude treadmill speed ramp-up. GRFs were filtered using a second-order bidirectional Butterworth filter with a 10 Hz cutoff frequency. Belt speed data were filtered using the same filter, but with a 30 Hz cutoff frequency determined through residual analysis [17]. All data were segmented into strides from left heel strike to subsequent left heel strike using a 10 N vertical GRF threshold, and normalized to 100 samples per stride. Strides were ensemble averaged to obtain representative GRF and belt-speed trajectories for each participant and speed. Stride duration per trial was calculated as the mean time interval between consecutive left-foot heel strikes.

2.3 Treadmill model fitting and validation

Treadmill model fitting and validation were performed using the normalized left-side speed and GRF trajectories. As for stride segmentation, swing phase was defined as periods when the vertical GRF was below 10 N. Before computing the delayed force

inputs, occasional small negative vertical GRF values, arising from measurement noise, and the corresponding AP GRF value were clipped to zero.

To initialize the controller, the predicted belt speed was set to the nominal treadmill speed during late swing (90% of the gait cycle). All subsequent belt speed values were computed recursively using Equation 1. Since belt speed was set to the nominal speed during swing, the final computed point matched the initialization point, ensuring a continuous belt-speed trajectory.

The free model parameters K_{F_x}, K_{F_y}, K_P, K_D, and t_d were identified by minimizing the mean square error (MSE) between the measured and predicted belt-speed trajectories in stance across the data used for each optimization. We performed the parameter optimization in Optuna [18] using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) sampler and 4000 parameter evaluations per optimization.

The generalizability of the model across walking speeds and across participants was assessed using leave-one-speed-out and leave-one-participant-out cross-validation, respectively. Eventually, a final parameter set was estimated from the full dataset and used in all subsequent simulations. All optimizations were repeated with three different random seeds, and the parameter sets yielding the lower overall MSE were selected as the final model parameters.

2.4 Optimal control gait simulations

We simulated gait using a 2D musculoskeletal model and two treadmill models: a realistic treadmill with intra-stride belt-speed variations, described above, and an ideal treadmill with constant belt speed. The sagittal musculoskeletal model of the lower limbs [19] comprised seven segments, 16 Hill-type muscles, and nine degrees of freedom. The model state was given by $\mathbf{x}(t) = \left[\mathbf{q}(t)\ \dot{\mathbf{q}}(t)\ \mathbf{l}_{\mathrm{CE}}(t)\ \mathbf{a}(t)\right]^T$, where $\mathbf{q}$ denotes the generalized coordinates, $\dot{\mathbf{q}}$ their velocities, $\mathbf{l}_{\mathrm{CE}}$ the contractile element lengths, and

194 **a** the muscle activations. Ground contact forces were computed using six smoothed
195 Hunt-Crossley contact spheres per foot [20]. Both treadmill models were implemented
196 by adding the belt speed to the AP velocity of each contact sphere [11]. The equations
197 of motion were obtained by combining the musculoskeletal and ground contact models.

198 Walking patterns were generated by solving optimal control problems, in which
199 an initial state $\mathbf{x}(0)$, muscle excitations $\mathbf{u}(t)$, and stride duration T are found that
200 minimize an objective function J subject to the system dynamics and additional con-
201 straints. Our objective function J consisted of weighted contributions from muscular
202 effort (J_{effort}) and tracking errors in joint angles (J_{angles}), and GRFs (J_{GRF}) (see
203 Appendix for details). The optimization problem was formulated as:

$$
\begin{aligned}
\min \quad & J = w_{\text{effort}} J_{\text{effort}} + w_{\text{angles}} J_{\text{angles}} + w_{\text{GRF}} J_{\text{GRF}} \\
\text{subject to} \quad & \mathbf{f}(\mathbf{x}(t), \dot{\mathbf{x}}(t), \mathbf{u}(t)) = 0 && \text{(system dynamics)} \\
& \mathbf{x}_{\min} \leq \mathbf{x}(t) \leq \mathbf{x}_{\max} && \text{(state bounds)} \\
& \mathbf{u}_{\min} \leq \mathbf{u}(t) \leq \mathbf{u}_{\max} && \text{(control bounds)} \\
& \mathbf{x}(T) = \mathbf{x}(0) && \text{(state periodicity)} \\
& \mathbf{u}(T) = \mathbf{u}(0) && \text{(control periodicity).}
\end{aligned}
\tag{5}
$$

204 For both treadmill models, the belt speeds $\mathbf{v}(t)$ were included as optimization
205 variables. For the ideal treadmill model, these speeds were constrained to the nominal
206 belt speed $\mathbf{v}_{\text{des}}$:

$$
\mathbf{v}(n) - \mathbf{v}_{\text{nom}} = \mathbf{0}, \quad 0 \leq t \leq T. \tag{6}
$$

207 For the realistic treadmill model, the belt speeds were constrained according to

$$
\mathbf{v}(n) - \mathbf{v}_{\text{tm}}(n) = \mathbf{0}, \quad 0 \leq t \leq T, \tag{7}
$$

where $\mathbf{v}_{\mathrm{tm}}(n)$ denotes the belt speed computed by the treadmill model (Eq. 1). Unlike the experimental implementation, no initialization point or recursive computation was required because the entire gait cycle was solved simultaneously. The ground contact model could sometimes lead to artifacts in the AP GRF during the loading response, which is a known problem in gait simulations [21]. In those cases, the AP GRF signal in that phase was interpolated using a cubic spline before passing it into the treadmill controller (see Appendix for example). Interpolation was applied only to the treadmill-controller input, whereas in the equations of motion the original GRFs were used. The optimal control problem was discretized using an implicit backward Euler scheme with $N = 100$ nodes and solved using direct collocation and IPOPT. Simulations were performed using biosym [22], a JAX-based python package for optimal control.

We created 15 musculoskeletal models by scaling a generic model to each participant's height and body mass. GRF tracking was based on participant-specific experimental data. As experimental joint kinematics were not available for our participants, joint-angle tracking was based on speed-specific normative gait kinematics from [23]. Specifically, we tracked the normal cadence data for lower speeds (1.0-1.4 m/s) and the high cadence data for faster treadmill speeds (1.6 and 1.8 m/s).

For each participant, a standing solution was used as the initial guess for walking on an ideal treadmill with low-stiffness contact spheres, as suggested by [24]. This low-stiffness solution was used as initial guess for the ideal and realistic treadmill simulations with increased stiffness. In total, this yielded 150 simulations for subsequent analysis, 75 for each treadmill type (15 participants $\times$ 5 walking speeds).

2.5 Evaluation of simulated treadmill effects

We evaluated the effects of the realistic treadmill by comparing simulated lower-limb kinematics and kinetics obtained with the realistic and ideal treadmill models throughout the gait cycle. Gastrocnemius and tibialis anterior activations were also

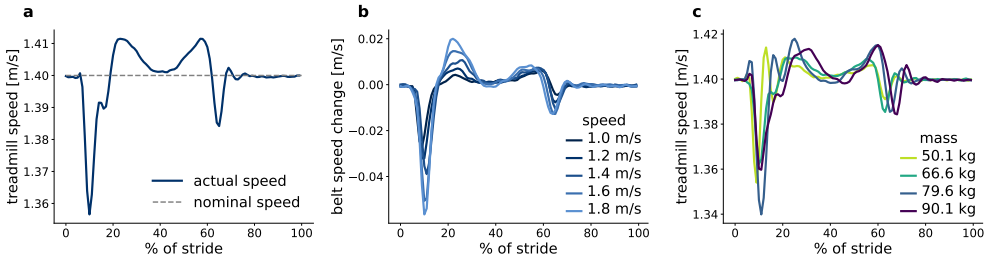

Fig. 2 Experimentally measured treadmill speeds. a: Exemplary belt-speed pattern: belt speed decreases after heel strike, overshoot during mid-stance, and decrease again around toe-off. **b:** same person, multiple speeds. **c:** multiple persons, same speed.

examined. These muscles have been shown to respond to minimal belt-speed perturbations applied at the beginning of stance, even when the perturbations were not noticed by participants [25]. Since the timing and amplitude of those perturbations were in the same range as the belt speed decrease after heel strike [2, 8], we expected similar compensatory effects in our simulations.

Finally, we computed the following discrete gait parameters: peak hip and knee extension moments, peak ankle dorsiflexion moment, relative metabolic rate [26], cadence, and hip and ankle ranges of motion (ROMs). In addition to comparing the two treadmill models, differences in these parameters were qualitatively compared with experimental treadmill-overground differences. Given the extensive literature on treadmill and overground walking, this comparison primarily focused on a recent meta-analysis synthesizing findings across multiple studies [4].

3 Results

3.1 Experimental data

We observed belt-speed deviations of up to 5.1% of the nominal belt speed in the processed data. Within participants, belt-speed profiles were similar across walking speeds but scaled with speed, whereas profile shapes differed considerably between participants, even at the same speed (Figure 2).

3.2 Validation and fitting of the realistic treadmill model

During cross-validation on experimental data, the model closely reproduced participant- and speed-specific belt-speed profiles for left-out participants and speeds (Figure 3). The stance-phase root-mean-squared-error (RMSE) between the predicted and measured belt-speed trajectories across all left-out trials was 0.0034 ± 0.0019 m/s for the leave-one-speed-out, and 0.0034 ± 0.0017 m/s for the leave-one-participant-out cross-validation. Fitting the final model to all available data resulted in an RMSE of 0.0029 m/s. The optimized parameters are reported in Table 1.

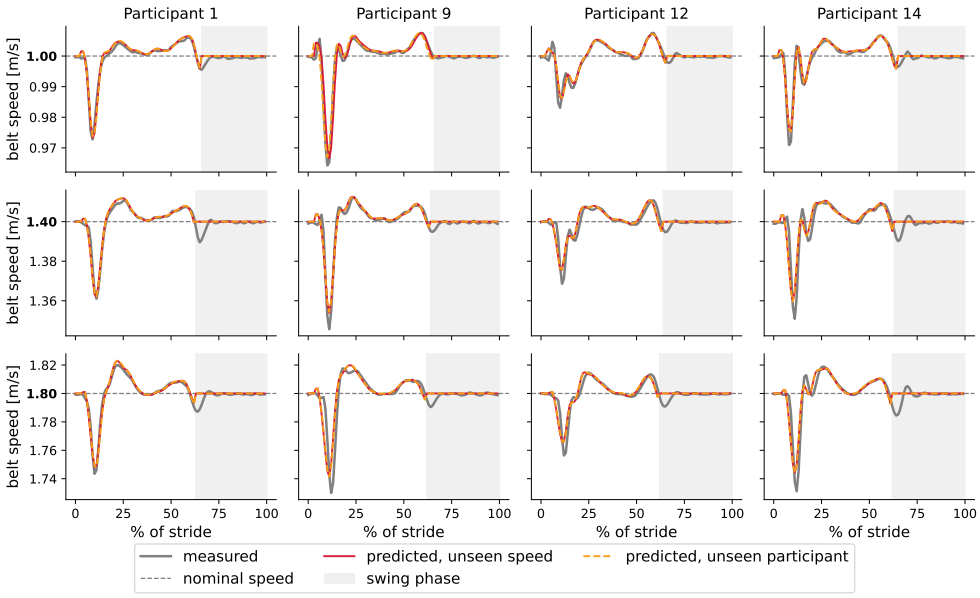

Fig. 3 Examples of measured and predicted treadmill belt-speed trajectories during leave-one-speed-out and leave-one-participant-out cross-validation. Columns show four representative participants, and rows show the slowest (1.0 m/s), intermediate (1.4 m/s), and fastest (1.8 m/s) walking speeds. In each subplot, the corresponding walking speed (red) or participant (orange) was excluded from parameter estimation.

Table 1 Optimized parameter values for the final realistic treadmill model. The parameters shown here are rounded to five significant digits for readability.

K_{F_x} [m/N]	K_{F_y} [m/N]	K_P [-]	K_D [s]	Delay [s]
4.1432×10^{-6}	9.2631×10^{-7}	0.6539	1.2843×10^{-16}	0.0519

3.3 Simulations

For 72 of the 75 simulation pairs, both the ideal and realistic treadmill simulations converged successfully. After additionally excluding pairs in which either simulation exhibited toe-walking, 68 simulation pairs remained for the analysis (see Appendix for details). The realistic treadmill model produced participant- and speed-specific belt-speed patterns in the simulations (Figure 4), similar to the experimental data.

Joint angles were highly similar between treadmill models (Figure 5). The realistic treadmill resulted in slightly greater knee flexion during early stance at all speeds, but the mean difference remained below 0.25° even at 1.8 m/s, where belt-speed variations were largest. Hip flexion was slightly greater around toe-off and in early swing, but the average difference over all participants was also never more than 0.14°. The maximum differences for individual participants were 0.69° for the hip, 1.06° for the knee, and 2.47° for the ankle angle. For the joint moments, in contrast, the realistic treadmill model led to differences mainly during the loading response, when belt-speed deviations were largest. Knee extension moments were higher and ankle plantarflexion

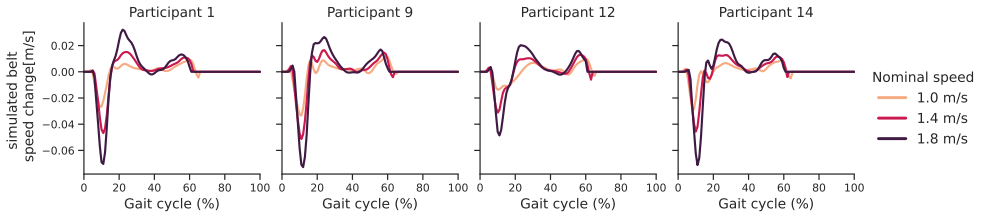

Fig. 4 The resulting simulated belt speeds for the same four exemplary participants shown in Figure 3 at the slowest, intermediate, and fastest speeds. Belt speed was not tracked in the optimal control simulations; instead, the belt speed deviation is emerging from the realistic treadmill controller.

moments lower with the realistic treadmill. Expressed as a percentage of the ideal-treadmill moment at the corresponding point in the gait cycle, differences decreased from 4.4% to 2.7% for the knee and increased from 2.7% to 13.1% for the ankle between 1.0 and 1.8 m/s. However, absolute differences remained small, increasing from 0.006 to 0.026 Nm/kg for the knee and from 0.009 to 0.056 Nm/kg for the ankle. Maximum individual differences were 0.062, 0.065, and 0.10 Nm/kg for the hip, knee, and ankle moments.

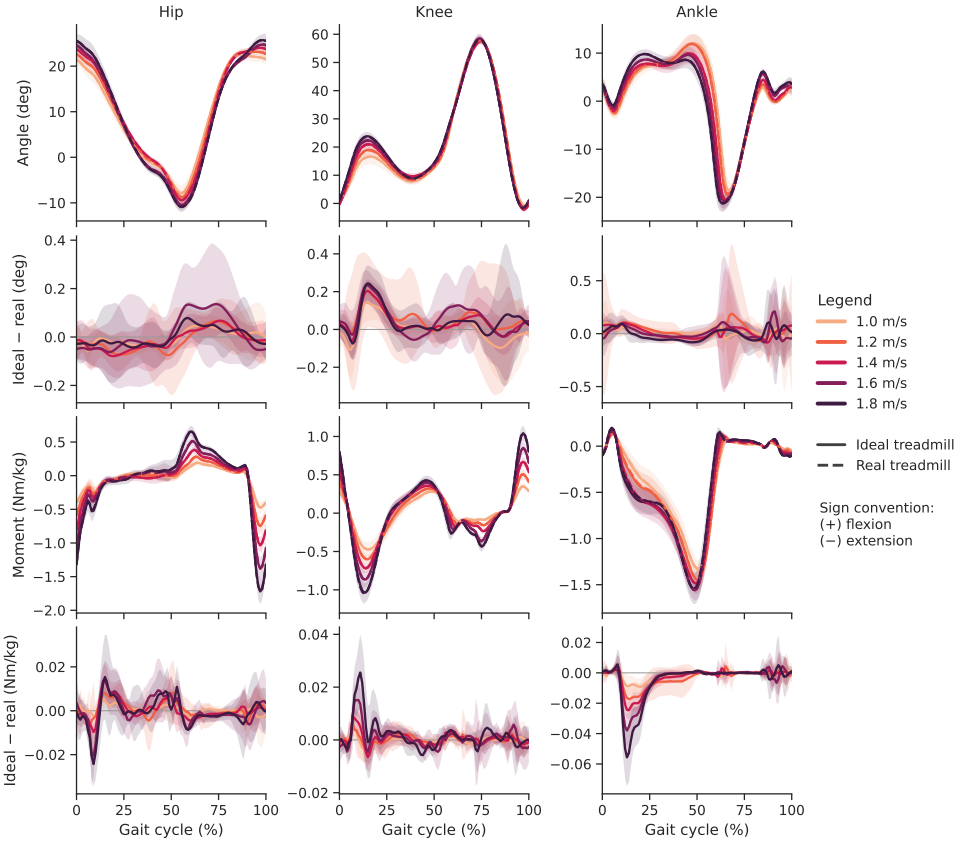

Fig. 5 Simulated lower-limb joint angles and joint moments for the ideal and realistic treadmill models, averaged across all valid participants and shown per walking speed. Shaded areas indicate the standard deviation. As the trajectories are often similar between the two treadmill models, the differences (realistic minus ideal) are shown separately in every second row.

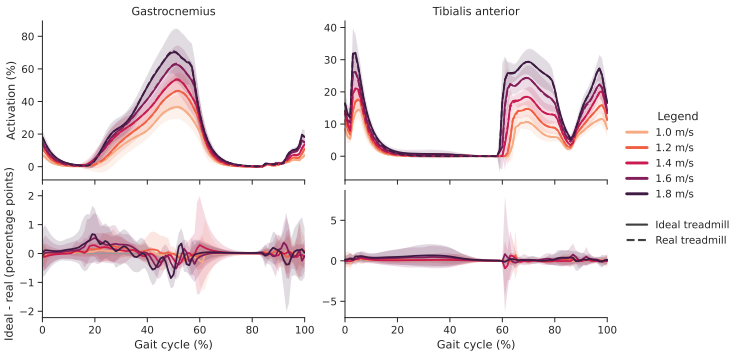

Fig. 6 Simulated muscle activations of the gastrocnemius and tibialis anterior muscles for the ideal and realistic treadmill models, averaged across all valid participants and shown per walking speed. Shaded areas indicate the standard deviation. As the trajectories are often similar between the two treadmill models, the differences (realistic minus ideal) are shown separately in the bottom row.

Gastrocnemius and tibialis activations were also similar between treadmill models, with mean differences below one percentage point (Figure 6). We found higher differences for individual participants, but the largest were around toe-off and may result from small timing shifts, such that the same sample was before toe-off in one condition and after toe-off in the other, resulting in large differences when comparing the same samples. During early stance, where we expected the biggest differences, we did not find consistent changes.

For the discrete metrics (Figure 7), relative metabolic rate was higher with the realistic treadmill in most cases, with a median difference of 0.063 W/kg across participants and speeds. Despite a few outliers, cadence was consistently lower, although the average difference was only 0.06 steps/min. However, with both treadmill configurations, the virtual participants were walking faster than our real participants. Differences in peak joint moments were also small. Peak hip extension moment was higher and peak ankle dorsiflexion moment was lower with the realistic treadmill, but mean differences per speed never exceeded 0.004 Nm/kg for the hip and 0.002 Nm/kg for the ankle. Peak knee extension moment was lower with the realistic treadmill at slower speeds, but this difference decreased and reversed at 1.8 m/s, where the mean

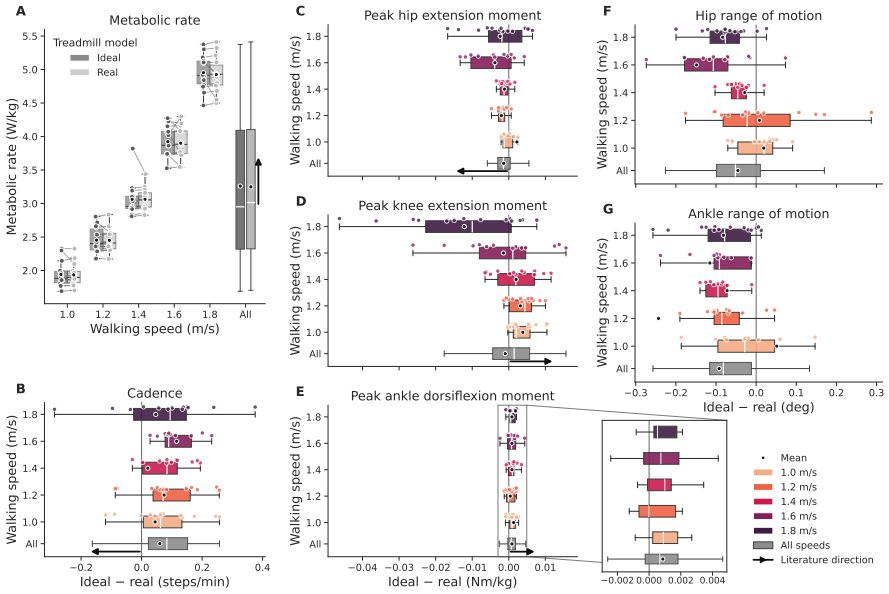

Fig. 7 Discrete metrics computed from the simulations. Metabolic rate (A) shows the absolute values, all other plots show the difference between the ideal and realistic treadmill simulations. For readability, individual outliers were excluded in the plot, but included for the computation of the statistics. Arrows indicate the direction of the respective treadmill–overground difference reported in the literature [4]. No arrows are shown for the ranges of motion because no significant treadmill–overground differences were reported.

difference was 0.012 Nm/kg. Hip and ankle ranges of motion were only slightly larger with the realistic treadmill, with median differences of 0.05° and 0.08°, respectively.

The direction of the simulated realistic-ideal treadmill differences agreed with that of experimentally reported treadmill-overground differences for metabolic rate and peak hip extension moment, which were higher on the treadmill, and peak ankle dorsiflexion moment, which was lower [4]. Peak knee extension moment showed the same direction as the literature only at lower walking speeds. No significant treadmill-overground differences in hip or ankle range of motion were reported in the meta-analysis, consistent with the small differences observed in our simulations. Cadence showed the opposite trend: while cadence has been reported to be higher during treadmill than overground walking [4], it was consistently lower with the realistic than the ideal treadmill.

4 Discussion

In this work, we proposed a novel model to predict treadmill belt-speed variations from GRF data. After validation on experimental data, we incorporated the treadmill model into an optimal control framework to determine the influence of realistic treadmill behavior on gait simulations compared with an ideal treadmill that assumes constant belt speed. Current gait simulations typically neglect intra-stride belt-speed variations. If the choice of treadmill model led to differences in the simulated gait patterns, future gait simulations may therefore benefit from incorporating realistic treadmill behavior. Finally, we compared differences between the realistic and ideal treadmill simulations with previously reported treadmill-overground differences. This allowed us to isolate the contribution of belt-speed variations from other factors that may contribute to treadmill-overground differences but cannot be separated in human experiments.

Our treadmill model accurately predicted participant- and speed-specific belt-speed deviations, including for unseen participants and speeds. We showed that, in contrast to previous suggestions, the magnitude of the belt-speed decrease after heel strike and the overall belt-speed profile depends on changes in GRFs rather than on GRF magnitude. Because our model relies only on GRF data, it allows estimating instantaneous belt speed in laboratories where belt speed cannot be measured, or retrospectively in studies where it was not recorded. The fitted model parameters may, however, differ for other treadmills, since previous work has shown that belt-speed variations differ between treadmill types [9]. The parameters may therefore need to be refitted once when applying the model to a different treadmill. We expect the underlying model structure to generalize across treadmills, but this remains to be tested. Future work should also investigate its applicability to running and very slow walking.

In simulation, the predicted joint angles and moments were highly similar between the realistic and ideal treadmill simulations. Differences in joint angles and hip and ankle ROMs were often below 1°, which is smaller than reported minimal detectable

changes for these variables [27]. Differences in joint moments occurred mainly during the loading response, when belt-speed deviations were largest. Although the ankle-moment difference reached 13.1% of the ideal-treadmill plantarflexion moment at 1.8 m/s, it did not affect the peak moment later in stance. Metabolic rate mostly differed by less than 1% of the ideal-treadmill value, compared with a reported minimal detectable change of approximately 7.7% for oxygen consumption during treadmill walking [28]. Differences above 7% occurred in only four of 63 simulation pairs and may be outliers. Cadence differences were also negligible. Even at 1.8 m/s, the maximum difference was less than 0.4 steps/min, corresponding to a difference in stride duration of only approximately 3 ms for a stride duration of 0.9 s. Thus, although realistic belt-speed dynamics produced systematic changes in some gait parameters, their effects on the overall gait predictions were small. Accounting for intra-stride belt-speed variations therefore appears unnecessary for simulations of normal walking, unless joint moments during the loading response are of particular interest. However, differences in peak hip extension moment and metabolic rate increased with walking speed and may become more relevant during running.

Despite their small magnitudes, most simulated changes were in the same direction as experimentally observed treadmill-overground differences, except for cadence. The meta-analysis used for comparison primarily reports standardized mean differences, preventing a direct comparison of the absolute magnitude of the simulated and experimental differences [4]. However, comparison with individual studies reporting absolute differences suggests that the simulated effects are smaller than experimentally observed treadmill-overground differences [1, 29]. Thus, belt-speed fluctuations may contribute to the direction of some treadmill-overground differences, but other factors, like psychological effects, may be more important.

Our study has limitations. We tracked the same joint angles for all participants because participant-specific kinematics were unavailable. However, the joint angle

tracking was weighted low in comparison to the GRF tracking term, which did track participant-specific data. Nevertheless, tracking kinematically consistent joint-angle and GRF data may improve the simulations. Although differences between treadmill models were small, it remains unclear which condition is more realistic. Direct validation is difficult because metabolic measurements are noisy and no ground truth exists for joint angles and moments. Our experiments used a dual-belt treadmill, and even though we assume that our model also works for single-belt treadmills, this remains to be tested. Finally, our treadmill is relatively new and high-powered, so we expect belt-speed deviations and their effects on simulated gait to be greater for older or lower-powered treadmills.

5 Conclusion

In this study, we developed and validated a computational model that accurately predicts instantaneous treadmill belt-speed variations throughout the stride from ground reaction force data. The model can be used to estimate belt-speed variations when direct measurements are unavailable and enables the incorporation of realistic treadmill dynamics into musculoskeletal simulations. Using this model, we showed that intra-stride belt-speed variations generally have only small effects on simulated gait kinematics, kinetics, and energetics. Therefore, accounting for these variations appears unnecessary in simulations of normal walking under comparable treadmill conditions, except when joint moments during loading response are of particular interest. Furthermore, although several simulated changes were consistent with experimentally reported treadmill-overground differences, their small magnitude suggests that belt-speed variations are unlikely to be a major contributor to these differences. Overall, our findings provide a basis for deciding when realistic treadmill dynamics should be incorporated into gait simulations and when the assumption of constant belt speed is sufficient.

Declarations

Ethics approval and consent to participate

The study was approved by the ethics committee of Friedrich-Alexander-Universität Erlangen-Nürnberg (Re.-No. 22-437-B) and conducted according to the Declaration of Helsinki. All participants provided written informed consent prior to participation.

Consent for publication

Not applicable.

Availability of data and materials

The experimental data needed to reproduce the results are available on Zenodo: https://doi.org/10.5281/zenodo.22711564. The source code for fitting and validating the realistic treadmill model, running the optimal control simulations, and reproducing the analyses and figures is available on GitHub: https://github.com/biomac-group/realistic_treadmill_sim.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

SF conceptualized the study, designed and implemented the computational model, conducted the simulations, analyzed and visualized the data and results, and wrote

the original draft. MG, AW, and ADK supported the study design, implementation, troubleshooting, and interpretation. ADK and BME supervised the project. All authors reviewed and edited the manuscript. All authors read and approved the final manuscript.

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Supplementary information.

- ***Supplementary Material***

  pdf. Implementation details.

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