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Optimal Integration of Hybrid FES-Exoskeleton for Precise Knee Trajectory Control

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Abstract— **This paper introduces a novel hybrid torque allocation method for improving wearability and mobility in integrated functional electrical stimulation (FES) of the quadriceps muscles and powered exoskeleton systems. Our proposed approach leverages a hierarchical closed-loop controller for knee joint position tracking while addressing limitations of powered exoskeletons and FES systems by reducing power consumption and battery size and by mitigating FES-induced muscle fatigue, respectively. The core component is a model-free optimization algorithm that dynamically distributes torque between FES and the exoskeleton by considering tracking error, effort, and the prediction of muscle fatigue in the cost function, computing allocation gain in an online manner. The online optimization approach interactively changes the optimal allocation gain by taking into account the instantaneous value of error and effort and also penalizing FES-induced fatigue, a common challenge in long-duration experiments. The results demonstrate that this dynamic allocation significantly improves system wearability by reducing power consumption without increasing muscle fatigue during the extension phase of walking. This hybrid control approach contributes to improving exoskeleton wearability and rehabilitation outcomes for individuals with SCI and mobility impairments, enhancing assistive technology and quality of life.**

I. Introduction

A. Background on Hybrid FES-Exoskeleton

Spinal cord injury (SCI), stroke, and other neurological conditions collectively affect millions of people worldwide, causing significant mobility impairments and impeding standing and walking activities [1]. Functional electrical stimulation (FES), a potential technology for restoring walking and standing after paralysis, has long held a recognized and indispensable role within the domain of physical therapy [2]. Characterized as a neurorehabilitative strategy that directly elicits and activates muscle function, FES offers not only functional training but also therapeutic advantages for people living with paralysis-related challenge [3]. Nevertheless, despite advancements in the application of FES, the rapid onset of muscle fatigue induced by FES remains a significant technical challenge due to the subsequent reduction in muscle force, which constrains the duration of walking activities [4].

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Powered exoskeletons, wearable robotic devices serving as an alternative rehabilitation technologies, have traditionally been developed to provide mechanical support and assistance to individuals dealing with conditions such as SCI, aiding them in regaining lower limb functions. These rehabilitative and assistive exoskeletons not only help users maintain independence but also improve their physical fitness. Notable examples of powered exoskeletons, including Indego [5], Exo H3 [6], ReWalk [7], HAL [8], and Ekso GT [9], have emerged in recent years, designed to assist and rehabilitate users. Nonetheless, although active exoskeletons are increasingly used in rehabilitation, their high energy consumption during walking necessitates considerable battery power and large motors, which limits their portability and wearability within the community [10].

Hybrid exoskeletons, combining a powered exoskeleton with an FES system, present a promising alternative that incorporates the advantages of both approaches and addresses their respective shortcomings [16]–[21]. The integration of FES and exoskeletons into hybrid rehabilitation systems can provide both functional and physiological benefits to patients, thereby enhancing the effectiveness and efficiency of rehabilitation [3]. In a typical FES system, muscle stimulation and contraction often lead to muscle fatigue and reduced precision of control [22]–[24]. Hybrid systems, in which the exoskeleton provides support and power while FES contributes additional torque, effectively address these limitations [25]. This collaborative approach creates a synergistic effect that enhances overall rehabilitation outcomes. Recent research highlights the potential of hybrid actuation, leveraging FES-induced muscle contractions and exoskeleton motors, to reduce muscle fatigue (in comparison to FES-only actuation) and motor weight (compared to powered exoskeletons) [26].

B. Cooperative and Shared Control

Despite the advantages of the hybrid exoskeleton, the combined use of FES and the electrical motor renders the exoskeleton actuator redundant [14]. Furthermore, the presence of two actuators with distinct dynamics complicates the synchronization process. Addressing actuation redundancy, differences in actuator dynamics, and managing the fatigue

TABLE I

RECENT STUDIES USED OPTIMAL CONTROL FOR HYBRID TORQUE ALLOCATION

Author	Application	Optimal Control Strategy	Cost Function Terms
Singh, et al (2024) [11]	Lower limb - Walking & knee extension	Model predictive control allocation	Error & torque
Dunkelberger, et al. (2024) [12]	Upper limb - Gripping & arm manipulation	Model predictive control	Error & torque
Iyer, et al. (2022) [13]	Lower limb - Knee extension	Online actor-critic identifier (RL)	FES current, motor torque, & error
Molazadeh, et al. (2021) [14]	Lower limb - Sit-to-stand	Predictive allocation strategy	FES & motor torque
Bao, et al. (2020) [15]	Lower limb - Sit-to-stand	Model predictive control	FES & motor torque & estimated fatigue
Kirsch, et al. (2018) [4]	Lower limb - Knee extension	Nonlinear model predictive control	Error & torque
Current study	Lower limb - Knee extension	Model-free optimization-based allocation	Error, energy, & accumulated fatigue

dynamics of FES presents complex control challenges that require a more structured control design to optimize the concurrent operation between FES and the electrical motor [27]. Cooperative and shared control have been employed in numerous studies to coordinate hybrid FES and motor actuation, utilizing various approaches, including nonlinear adaptive control families and optimal control methods [4], [11]–[15], as well as in references [18] and [10], [28]–[31]. Ha et al [18] and Quintero et al [31], utilized an adaptive controller for the hybrid integration of FES and electric motors for walking and knee regulation. In Ha et al. [18], joint torque profiles from earlier steps were used by the muscle control loop to adjust the muscle stimulation profiles for subsequent steps, while Quintero et al. [31] employed a PD controller to regulate the electric motors. Simultaneously, a proportional gain modulated the stimulation, with its adaptation depending on the current supplied to the electric motor [31].

Optimal control has garnered considerable attention in the literature as a viable approach for coordinating the cooperative control of FES and an electric motor in hybrid exoskeleton systems [4], [10]–[15]. A range of variations of optimal control methods have been employed to optimally distribute torque between FES and an electric motor for different applications, ranging from upper body exoskeletons [12] to lower limb exoskeletons for knee extension [4], [13], walking [11], and sit-to-stand tasks [14], [15]. Except for Reinforcement Learning (RL)-based optimal torque control approaches [13], most other studies employed model-based linear or nonlinear optimization programming to solve this problem. The cost functions in these optimal control methods were quadratic and consisted of different terms, including tracking or regulation error, FES, motor, or both torques, and sometimes an estimated value for muscle fatigue. A similar structure and terms were used in the RL approach for the reward function. A summary of the most recent optimal torque allocation approaches is provided in Table I. Despite their success in optimally distributing torque between FES and electrical motors, there are two drawbacks to these approaches. First, all optimizations are model-based. Even in the case of RL-based approaches (e.g., [13]), a simulator (a model of the hybrid exoskeleton) was used for training the algorithm. Secondly, none of these studies considered energy consumption in their cost function.

FES requires less energy compared to an electrical motor, while its trajectory tracking error is higher than in the motor-only case [4]. Therefore, there is a clear compromise between FES and motor contributions to minimizing required energy or tracking error. These optimization-based methods focus on minimizing FES torque; however, the magnitude of FES torque is not necessarily an accurate indicator of energy consumption or fatigue. If the design objective is to minimize the weight and size of the exoskeleton, energy minimization must be prioritized over torque minimization. This argument is grounded in the fact that FES-induced torque does not consume the same portion of energy as a motor does. While FES-induced torque is proportional to the stimulation current, this current is solely used to trigger muscle movement. In other words, FES is more energy-efficient than electrical motors since it uses human muscle energy to move the body. This is the reason why FES energy must be used in the optimization cost function instead of FES torque.

C. Contribution

To address the aforementioned drawbacks and exploit the strengths of both actuation types, we propose a model-free optimization-based torque allocation between FES and electrical motor, incorporating tracking error, energy consumption, and FES-induced muscle fatigue terms in the cost function. The online implementation of this optimization accounts for instantaneous changes in the cost due to variations in error, energy consumption, and, in particular, fatigue terms. This capability enables interactive changes in allocation gain in response to the dynamic behavior of the system and penalizes fatigue induced by FES. The proposed method enhances the wearability of the hybrid exoskeleton, makes it more personalized, and minimizes muscle fatigue in continuous and long-duration experiments. The main contributions of this paper are threefold:

- Inclusion of total energy consumption by both actuators in the optimization cost function.
- Online implementation of a model-free optimization for torque allocation, resulting in a dynamic allocation algorithm.

- Designing a personalized cost function by tuning person-specific weights in the cost function.

II. Methods

The primary goal of the hybrid closed-loop control framework was to distribute torque between actuators to reduce total energy consumption and minimize tracking error (Figure 1). A proportional–integral–derivative (PID) controller calculated control torque based on tracking error in a position control loop. This torque was then allocated between two actuators using an online-computed allocation gain to minimize the combined error, energy, and muscle fatigue index. Additionally, an inverse model of the FES as an actuator was employed to convert the output torque of the low-level controller into electrical stimulation current.

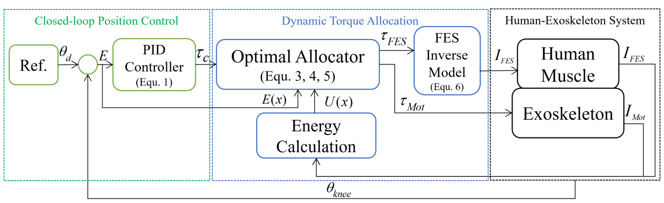

Fig. 1. Schematic of the proposed hybrid dynamic torque allocation control

A. PID Feedback Control

A position control loop, utilizing a PID controller (PID Controller block in Figure 1), ensured that the knee joint in the hybrid exoskeleton system followed the desired reference trajectory. The control torque (τ_c) calculated by the PID controller was determined by the formula:

$$\tau_c = K_p \cdot e + K_i \cdot \int edt + K_d \cdot \frac{de}{dt} \tag{1}$$

K_p, K_i, and K_d denote the proportional, integral, and derivative gains of the controller, selected empirically to minimize tracking errors and mitigate jerky movements from overshoots. The calculated τ_c was forwarded to the subsequent torque allocator block, serving as a low-level controller for torque distribution among actuators.

B. Optimization-based Torque Allocation

Following the control part, an optimization-based torque allocation approach was developed to enhance real-time torque distribution in the control framework. This strategy considered tracking error, total energy consumed by both actuators, and estimated muscle fatigue, computing the instantaneous optimal allocation gain x at each time-step, which served as the contribution of each actuator. Thereby, the allocation was defined as a quadratic programming problem as shown below:

$$\begin{aligned} J(x_k) &= \sum_{i=1}^{k} E_i(x)^2 + p \cdot U_i(x)^2 + \gamma \cdot F_i(t,x)^2 \\ \text{s.t. } & 0 \le x_k \le 1 \end{aligned} \tag{2}$$

where $J(x_k)$ is the instantaneous cost at time-step k, and $E_i(x)$, $U_i(x)$, $F_i(t,x)$ represent tracking error, total energy consumed by both actuators, and the accumulative index for muscle fatigue, respectively. p and γ are unknown weights in the cost function which determine the contribution of each component of the cost function (error, energy, and fatigue) in the cost value. The optimization variable, x, was constrained to be between 0 and 1, determining none and full FES contribution in total torque respectively. This optimization must be solved online based on a stream of information (error, energy, and fatigue estimation) so that the computed optimal allocation gain can interactively adjust each actuator's contribution in total control torque.

In cost function design, the weights p and γ are unknown and vary depending on system dynamics. In a hybrid exoskeleton, individual human dynamics, including physical properties and muscle responses, make the system unique to each person. Thus, weight determination in the cost function must be personalized. The p weight emphasizes total energy compared to other factors and has lower variance than the γ weight. The latter reflects the fatigue index's contribution and is not only person-specific but also time-dependent, making it challenging to determine accurately due to limited ground-truth data of fatigue and the simplicity of the fatigue index prediction model. Therefore, the γ weight was empirically adjusted during experiments, while the p weight was tuned using offline optimization.

Therefore, in summary, the optimization-based torque allocation involved two steps:

- An offline optimization determines the p weight in the cost function using data from fixed allocation experiments.
- An online step dynamically determines allocation gain through an online optimization over a data stream and applies the designed cost function from step 1.

Step.1: Offline Optimization. The offline optimization aimed to determine the p weight in the cost function, ensuring convexity and achieving a minimum at the desired allocation value (x_d). To exclude the fatigue effect (the $\gamma \cdot F_i(t,x)^2$ term in the cost function), this step was conducted using the results of a short-term experiment where the muscle fatigue effect is negligible, and the cost function includes only the error and energy terms. Thus, the cost function for the offline optimization was defined as:

$$\begin{aligned} J(x) &= \sum_{i=1}^{m} E_i(x)^2 + p \cdot U_i(x)^2 \\ \text{s.t. } & 0 \le x \le 1 \end{aligned} \tag{3}$$

Here, $J(x)$ represents the total (final) cost of a batch dataset as opposed to the instantaneous cost in online optimization. In these experiments, the allocation gains were fixed at different values between 0 and 1. After conducting experiments with various fixed allocation gains, the desired energy reduction was chosen, taking into account exoskeleton design constraints. A convex cost function was then designed based on the desired allocation gain x_d, ensuring that the minimum of the cost function corresponds to x_d. A combined search and optimization method, detailed in Algorithm 1, determined the optimal value for the weight p in the cost function. Once convergence was achieved, the computed weight (p^*) was used in online optimization for dynamic torque allocation.

Algorithm 1: Combined offline optimization and search for computing weight p^* in the cost function

```
Data: Results of fixed allocation tracking
      experiments
for k = 1,2,... do
    J_k(x) = Σ_{j=1}^{k} E_j(x)^2 + p · U_j(x)^2
    s.t. 0 ≤ x_k ≤ 1
    Convexity check of J_k(x)
    x_k^* = argmin J_k(x);
    δ_k = x_k^* − x_d;
    p_{k+1} = p_k − α · δ_k;
    if |p_{k+1} − p_k| < ε then
        break
    end
end
```

Step.2: Online Optimization. In this step, the dynamic allocation gain computed at each time step determines each actuator's contribution to control torque based on the instantaneous cost, which was a sum of costs from the beginning until that time step. Because the online optimization algorithm utilizes instantaneous cost, any changes in error, energy, and fatigue index can influence the optimal allocation gain, meaning that the allocation gain changes interactively based on the instantaneous compromise between different factors. This interactive response in optimal gain resulted in a dynamic allocation approach that took into account dynamic changes in various aspects of the system, including error, energy, and specifically the accumulated fatigue index. The accumulated muscle fatigue index, $F_i(t,x)$, based on a simple prediction strategy calculated as follows:

$$F_i(t,x) = \sum_{i=1}^{n} x \cdot (1 - e^{-k_f(t-t_{\text{onset}})}) \tag{4}$$

Here, t represents time, t_{onset} is the onset time when fatigue initiates in the muscles, and k_f is the exponential decay gain fitted to the reduced joint motion due to muscle fatigue ($\theta_f = \theta \cdot e^{-k_f(t-t_{\text{onset}})}$). The multiplication by x (allocation gain) emphasizes the correlation between FES contribution and muscle fatigue. The computed optimal $x(t)$ at each time t was used to distribute torque between the electrical motor and FES. Since only the quadriceps muscle group was stimulated using FES, FES torque only existed in the knee extension direction, i.e., hybrid torque allocation only occurred during knee extension, while knee flexion was executed using the electrical motor. Therefore, torque distribution was based on a simple state machine, and the allocation gain was computed using the optimization program as shown below:

$$\begin{cases} \begin{cases} \tau_{\text{FES}}(k) & = x(k) \cdot \tau_{\text{c}}(k) \\ \tau_{\text{Mot}}(k) & = (1 - x(k)) \cdot \tau_{\text{c}}(k) \end{cases} & \text{if extension} \\ \tau_{\text{Mot}}(k) = \tau_{\text{c}}(k) & \text{else} \end{cases} \tag{5}$$

Here, $\tau_{\text{c}}(k)$ represents the total torque required to move the hybrid system to the desired position at time step k. $\tau_{\text{Mot}}(k)$ and $\tau_{\text{FES}}(k)$ denote the allocated torque to the motor and FES, respectively. Subsequently, the FES torque were forwarded to the inverse model to calculate the muscle stimulation current (See Optimal Allocator block in Figure 1).

C. FES Inverse Model

The torque allocation block generated two torque values for each actuator, including FES. However, the torque-current relationship in FES is not linear as is the case with an electrical motor. In the literature, various modeling approaches have been employed to describe the torque-current relationship in FES, including muscle activation, biomechanics, and non-parametric model learning [4], [32]. To reduce computational burden, a simple nonlinear regression model described the current-torque relationship in FES (Inverse FES Model block in Figure 1):

$$I_{\text{FES}} = I_0 + I_1 \cdot \tau_{\text{FES}} + I_2 \cdot \tau_{\text{FES}}^2 \tag{6}$$

Here, I_0, I_1, and I_2 are constant parameters to be experimentally estimated, and τ_{FES} and I_{FES} represent FES torque and current, respectively. For FES-induced torque measurement, a gravity model for the human shank and exoskeleton was employed. This gravity torque model, based on joint angle measurement in a steady-state holding test (at different angles), is described as:

$$\tau_{\text{gravity}} = G \cdot \sin(\theta) \tag{7}$$

Here, θ is the joint angle measurement, and G is a lumped constant parameter identified through experimentation.

III. Experiment

The experimental set-up depicted in Figure 2 was employed to assess the efficacy of our proposed dynamic torque allocation method. The Indego exoskeleton (Parker Hannifin Corporation, USA), equipped with a built-in FES system, was used in these experiments. One neurologically intact person (30 years old, male, height 1.81m, weight 78kg) tested the control strategy while seated with the knees at a 90° angle. The tester was instructed to relax their shanks, avoiding intentional movement. Two FES electrodes were placed on the quadriceps muscle group of one leg, and straps ensured stability during electrical stimulation. In this experiment, all online and real-time simulation and control computations were executed using the Simulink Real-time toolbox of MATLAB® software (MathWorks, Natick, MA, USA), version 2023, and sent to the exoskeleton in real-time through the CAN communication protocol (CAN bus).

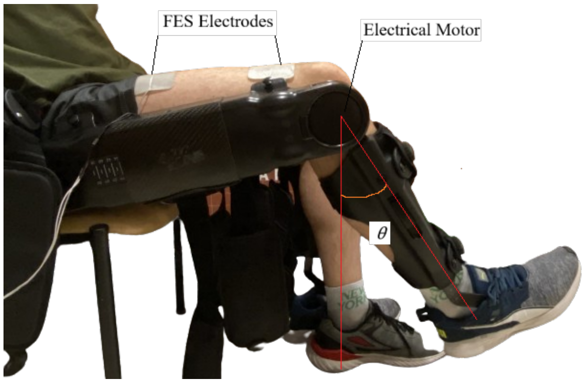

Fig. 2. Experimental set-up of hybrid FES-Exoskeleton

A. Parameter Estimation

To implement hybrid control and dynamic allocation, it was essential to identify parameters for the FES inverse model, gravity torque model, and muscle fatigue estimation model.

For gravity model identification, steady-state experiments were conducted, holding the human shank in the exoskeleton at specific angles within the knee motion range (from 5 to 40 degrees). A nonlinear curve fitting of known motor torque and corresponding gravity torque yielded the G parameter. Similar experiments were conducted for the FES inverse model, where FES acted as the actuator for holding the system at a specific angle. FES torque was considered equivalent to the gravity torque estimated using (8). Muscle fatigue parameters were estimated through experiments involving square-wave biphasic stimulation (40 mA amplitude, 16 Hz, and 400 µs pulse width) applied to the quadriceps muscle during a 5-minute test with a frequency of 0.5 Hz. A significant reduction in joint angle amplitude, starting at 50 seconds (coinciding with tester muscle fatigue), was observed. An exponential decay model was fitted to the knee joint angle decay, yielding the k_f parameter. Estimated parameters are listed in Table II.

TABLE II

PARAMETER ESTIMATION OF FES FATIGUE AND INVERSE MODEL

$G[kg.m/sec^2]$	4.01	$I_0[mA]$	21.224
k_f	0.0018	$I_1[mA/N.m]$	9.215
$t_{\text{onset}}[sec]$	50	$I_2[mA/N^2.m^2]$	0.2684

B. Fixed Allocation Results

To determine the optimal value of the parameter p in the cost function, multiple sinusoidal trajectory tracking experiments were conducted, each lasting 200 seconds. In these experiments, the shank was not held at a constant angle but oscillated around 20 degrees with an amplitude of 10 degrees. The sinusoidal trajectory is based on the principles of Central Pattern Generators (CPGs), which produce rhythmic, oscillatory patterns that control cyclic movements, such as walking or running, in a smooth and stable manner [3]. By selecting a sinusoidal trajectory, the reference input mimics the natural oscillatory behavior generated by CPGs, ensuring that the knee joint's movement aligns with the rhythmic patterns typically required in locomotion tasks. Since fatigue in this experiment begins around the 50th second ($t_{\text{onset}} = 50$ sec), selecting a 200-second duration provided a significant joint motion reduction of approximately 24% (see equation (4)), while also ensuring a tolerable length of electrical stimulation for the neurologically intact tester. Specifically, choosing a 100-second duration would result in only a 9% motion reduction, which is insufficient, while extending the experiment to 300 seconds would increase the reduction to 36%, making the experiment difficult to tolerate. Therefore, a 200-second duration was chosen as a suitable length for the experiment.

Torque allocation gain, denoted as x, varied from 0 to 1 across experiments, was held at fixed values within each. This variation aimed to observe how allocation gain influences root mean square error (RMSE) of tracking and total energy consumption by FES and motor. Table III displays the results, including RMSE and total consumed energy over a fixed 50-second window. Based on the dataset in Table III, a desired energy reduction of approximately 20 to 30% compared to the motor-only case guided the selection of the derived allocation value, set as $x_d = 0.35$, which based on fixed allocation tests can meet both energy reduction requirement while results in good tracking accuracy. Subsequently, by executing Algorithm 1, the optimal value for the cost weight was determined as $p^* = 99.7$, and this value was utilized in the dynamic allocation process. Figure 3 shows cost function plot for different p^* values.

TABLE III

FIXED ALLOCATION SIN TRACKING RESULTS

Allocation Gain x	RMSE of Sin Tracking [deg]	Total Consumed Energy [J]
0.0	2.96	30.1
0.2	2.79	24.3
0.35	2.89	22.7
0.45	3.15	23.5
0.70	3.69	22.7
0.85	4.27	24.3
1.0	5.11	25.8

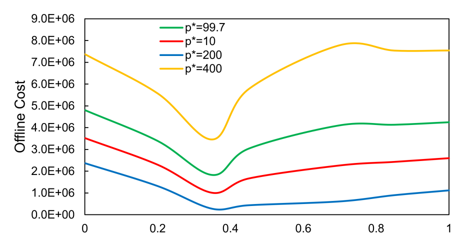

Fig. 3. Offline cost function is plotted for different p^* values. As it is shown the best cost function in terms of convexity and having a global minimum point at $x_d = 0.35$ is the one with $p^* = 99.7$

C. Dynamic Allocation Results

Similar to the experiment described in III-B the same sinusoidal trajectory was selected for the trajectory tracking experiment, which lasted 200 seconds and was conducted using dynamic torque allocation calculated by running the online optimization in (3). The weight term γ in the dynamic cost function was empirically set to 1.5. The results of the online computed allocation gain and sinusoidal trajectory tracking are shown in Figures 4 and 5, respectively.

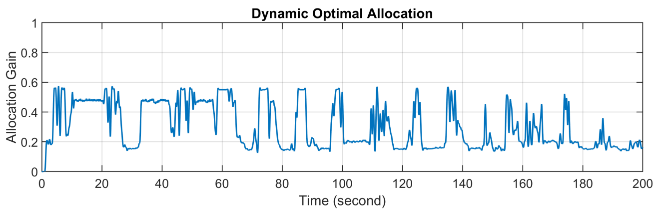

Fig. 4. Dynamic allocation gain computed using the online optimization

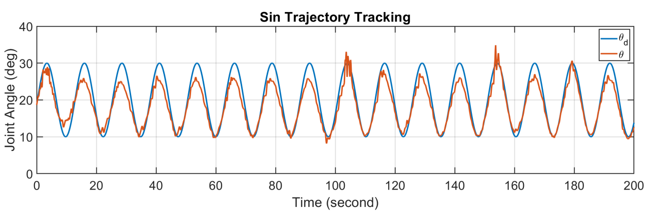

Fig. 5. Sin trajectory tracking using dynamic torque allocation

The RMSE of dynamic trajectory tracking and the total energy consumed over a 50-second window are 2.59 degrees and 23.5 joules, respectively.

IV. Discussion

The optimization-based dynamic torque allocation method successfully tracked the sinusoidal trajectory in knee joint motion while optimally distributing control between the FES and the electric motor.

In offline optimization experiments, it was evident that the total energy consumption in hybrid cases was lower than in the motor-only case, highlighting the significance of employing a hybrid FES-motor control for energy reduction, ultimately leading to a smaller size and lighter battery. Specifically, a higher FES contribution corresponded to increased energy efficiency. However, in the FES-only case, where the sole motor operates in the flexion direction (due to the unidirectional force from FES) and FES is used for extension, lower tracking accuracy resulted in increased fluctuation. As a consequence, motor motion in the opposite direction also increased. Consequently, in pure FES mode, not only was the RMSE higher, but energy consumption was also higher compared to most other allocation gains (e.g., x = 0.70 or 0.45). Another noteworthy trend observed in the fixed allocation tracking data was the increasing RMSE of trajectory tracking with the rise in allocation gain. This increase was attributed to the growing FES contribution. The FES actuator model used in the algorithm exhibited more uncertainty than the motor model, and the time-varying nature of muscle behavior introduced additional inaccuracies in trajectory tracking when using FES. Consequently, a higher FES contribution led to more errors in tracking.

In dynamic allocation mode, an online torque allocation algorithm was employed to compute a dynamically changing allocation gain. This gain varied in response to changes in cumulative error and energy at each time-step. These variations were primarily due to the sinusoidal reference trajectory, causing differences in the position control loop error, and the time-varying nature of muscle behavior. Importantly, the online optimization cost function included a term for the cumulative fatigue index. Therefore, after 50 seconds (the onset time of muscle fatigue), the value of the instantaneous cost gradually increased, and the gain gradually decreased. This led to a reduction in muscle contribution. The RMSE of trajectory tracking results indicated that this reduction in FES contribution had a positive impact on error reduction compared to a fixed allocation gain. However, due to increased motor contribution, the total amount of consumed energy also increased in comparison to the fixed value of x. This demonstrates the effectiveness of dynamic allocation, which not only considers instances of changes in energy consumption and error but also, by gradually reducing muscle contribution, helps mitigate muscle fatigue in long experiments.

This novel dynamic torque allocation method not only optimizes the balance between FES and motor torque but also represents a significant advancement in the development of more energy-efficient, lightweight, and portable exoskeleton systems. By employing this allocation method to design the system optimally, the need for large batteries and bulky components is reduced, thereby enhancing the wearability and practicality of exoskeletons for everyday use. The implications of these findings extend to the design of next-generation wearable technologies, where reducing battery size and improving portability are crucial for practical, real-world applications.

V. Conclusion and Future Works

This study addressed the torque sharing challenge between FES-induced muscle contraction and an electrical motor for precise knee joint trajectory tracking. The proposed method employed an online optimization-based approach to dynamically allocate torque between FES and the motor using PID feedback control. By incorporating total energy consumption, tracking error, and an accumulative fatigue index into a quadratic cost function, the approach optimally determined the contribution of each actuator, minimizing combined energy consumption and closed-loop error while considering muscle fatigue. Results demonstrate the method's effectiveness in reducing energy consumption and mitigating muscle fatigue. However, a limitation exists as the relationship between error and allocation gain is estimated linearly during optimization. Another limitation is empirically adjusting the γ weight during online optimization experiments, which can be done in a more systematic manner (e.g., using an adaptive rule). Improvement through online and data-driven learning is anticipated. A future direction could involve replacing the PID controller with an adaptive model-free control for enhanced adaptability to changing system dynamics while remaining model-free in both control and allocation.

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