

# Trajectory Tracking Enhancement for Lower-Limb Exoskeletons via Particle Swarm Optimization-based PID Control

**Van-Nam Vu<sup>1</sup>, Kim-An Hoang<sup>1</sup>, Tuan-Dat Nguyen<sup>1</sup>,  
Tran Kim Thanh<sup>2</sup>, Nguyen Ba Kha<sup>2</sup>, N.-K. Nguyen<sup>1\*</sup>**

<sup>1</sup>*Faculty of Control and Automation, Electric Power University, Hanoi, Vietnam*

<sup>2</sup>*School of Electrical and Electronic Engineering (SEEE), Hanoi University of Industry, Hanoi, Vietnam*

**ABSTRACT:** In the past decade, exoskeleton robots have become an attractive solution to helping and augmenting human mobility over functional rehabilitation. Besides medical and healthcare fields, advanced robotic systems may also be applicable in challenging areas like heavy industries or military. In this article, an optimal control approach is introduced to deal with the trajectory tracking tasks of the flexion-extension motions at hip and knee joints for two-degree-of freedom (2-DOF) lower-limb exoskeleton. A PID controller is then developed from the dynamic Lagrange derived model and subsequently tuned by using the Particle Swarm Optimization (PSO) algorithm. An important extension of our approach is the formulation of ITAE as objective function for PSO based tuning. The controller can address both system stability and response speed effectively and long-term tracking errors are greatly reduced, as the ITAE criterion is minimized. The effectiveness of the design control scheme is verified by MATLAB/Simulink simulations with strict quantitative criteria, such as overshoot, settling time and RMSE (Root Mean Square Error). Simulation results show that the PSO-PID controller achieves smoother system operation, faster oscillation suppression and remarkable tracking accuracy compared with conventional PID tuning techniques.

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## I. INTRODUCTION

Biomedical robotics has progressed enormously in the past decade, especially with an explosive welfare of exoskeleton systems. These systems have demonstrated significant value in therapist-assisted rehabilitation for stroke and spinal cord injury patients, as well as improved mobility and reduced physical stress for workers in manual labor environments [1-2].

Despite its high potential, a precise and reliable control strategy to control lower-limb exoskeletons is still a prominent technical problem. This is because of the extremely nonlinear behavior exhibited by human musculoskeletal system and also due to time-varying dynamic parameters in particular moment of inertia that vary during the flexion/extension of hip and knee joints.[3] Accordingly, how to accurately track the trajectory in such a complex and time-varying environment is still an important research problem.

In order to simulate those interactions, energy-based techniques such as the Euler–Lagrange formulation are usually used since they allow a clear expression of the dynamics of multi-rigid-body systems[4]. This approach allows the creation of mathematical models that describe complex dependencies between body motion, forces, and torques in lower limb exoskeleton systems.

Yet, the establishment of a realistic dynamic model is just one part of the design process. At the heart of this, designing a controller that can guarantee tracking of the desired trajectory with bounded errors in presence of non-linearities and time-varying parameters is very challenging[5].

In numerous practical applications, the fourth controller, which is PID controller is being used as it has simple structure and easy to implement[6-7]than other controllers without affecting stability. However, the selection of PID parameters (i.e., K<sub>p</sub>, K<sub>i</sub>, and K<sub>d</sub>) for extremely non-linear systems like exoskeletons is not trivial.

It is found that classical tuning techniques (such as the Ziegler–Nichols and trial and- error methods) are time-consuming, depend to a large extent on the designer's experience, and fail to provide a good tradeoff between fashionable response speed and system stability[8]. Under a poor selection of PID parameters, the system is likely to have severe oscillations with large overshoots and slow responses, which might be significantly detrimental to the performance and safety of human users in real practice[9].

To address the above shortcomings, this work presents a PSO based PID optimum method. Particle swarm optimization (PSO) is a population-based global search-based nature-inspired metaheuristic method[10] and widely used for finding the global optimum for complex, high-dimensional parameter space[11].

The major contribution of this work is proposing the Integral of Time Weighted Absolute Error (ITAE) as cost function to be used in PSO-based PID tuning[12]. The ITAE criterion is different from the well-known performance measures such as MSE or IAE because it penalizes longer time errors of the transient response to a larger extent[13]. Thereby, the optimization process inherently promotes shorter rise times and faster eradication of steady-state errors, which is consistent with enhanced tracking accuracy as well as overall system stability.

Extensive simulation studies have been performed in the MATLAB/Simulink, with a detailed comparison between PSO–PID and other conventional controllers [14–15] based upon performance criteria like overshoot, settling time and root mean square error (RMSE). The standards enable a comprehensive measurement of both transient response and trajectory tracking performance.

Anticipated results the expected results of this study are expected to provide a scientific basis for the intelligent control of exoskeletons in practice to manage smooth, stable and accurate assistance with motion, promoting safety and effectiveness in practical rehabilitation and mobility support.

## II. MATHEMATICAL MODEL OF A TWO-DEGREE-OF-FREEDOM LOWER EXOSKELETON

A model of 2-DOF lower exoskeleton is illustrated in Fig. 1. This model consists of two joints as follows:

- Hip joint is responsible for the flexion and extension motion of the thigh.
- Knee joint might be responsible for the flexion and extension motion of the shank.

In the proposed model, other complex joint motions, such as abduction/adduction and internal/external rotation, are intentionally neglected. This simplification allows the analysis to focus on reproducing the fundamental gait trajectory within the sagittal plane.

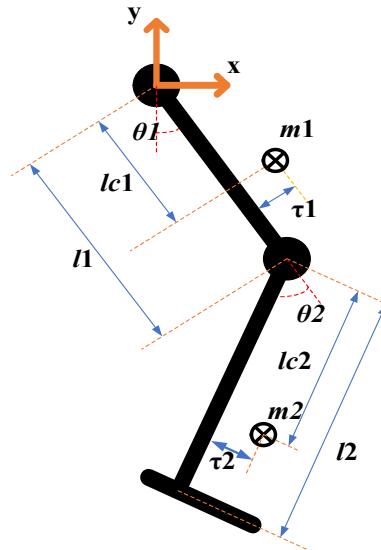


Fig. 1. Coordinate frames and Denavit–Hartenberg (D–H) parameters

### 2.1. Kinematics of the Two-Degree-of-Freedom Lower-Limb Exoskeleton

#### 2.1.1. Forward Kinematics

Table 1. D–H parameters of the two-degree-of-freedom lower-limb exoskeleton

Link i	$\theta_i$	$d_i$	$L_i$	$a_i$
(Hip)	$\theta_1$	0	L1	0
(knee)	$\theta_2$	0	L2	0

Based on the D–H parameter table and by sequentially multiplying the individual transformation matrices  $T_2^0 = A_1(q_1) \cdot A_2(q_2)$ , the overall homogeneous transformation matrix describing the pose of the terminal link (foot) is obtained as follows:

$$T_2^0 = \begin{bmatrix} \cos(\theta_1 + \theta_2) & -\sin(\theta_1 + \theta_2) & 0 & L_1 \cos \theta_1 + L_2 \cos(\theta_1 + \theta_2) \\ \sin(\theta_1 + \theta_2) & \cos(\theta_1 + \theta_2) & 0 & L_1 \sin \theta_1 + L_2 \sin(\theta_1 + \theta_2) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

By extracting the last column of  $T_2^0$ , the end-effector position in the Cartesian space (Px, Py) can be determined. These expressions are subsequently employed in the kinematic simulation block.

$$P = \begin{bmatrix} P_x \\ P_y \\ P_z \end{bmatrix} = \begin{bmatrix} L_1 \cos \theta_1 + L_2 \cos(\theta_1 + \theta_2) \\ L_1 \sin \theta_1 + L_2 \sin(\theta_1 + \theta_2) \\ 0 \end{bmatrix} \quad (2)$$

Where:

- Px, Py denote the horizontal and vertical coordinates of the ankle joint, respectively.
- $\theta_1, \theta_2$  represent the rotation angles of the hip and knee joints.
- L1, L2 correspond to the lengths of the thigh and shank links..

### 2.1.2. Inverse Kinematics

Knee joint angle  $\theta_2$ : Based on the law of cosines, the knee flexion angle is uniquely determined under the physiological configuration of the human knee joint, as expressed below:

$$\theta_2 = \arccos \left( \frac{x^2 + y^2 - L_1^2 - L_2^2}{2L_1L_2} \right) \quad (3)$$

Hip joint angle  $\theta_1$ : Based on geometric projection and the previously obtained value of  $\theta_2$ , the hip joint angle is computed to ensure the correct orientation of the robotic leg, as given by:

$$\theta_1 = \text{atan2}(x, -y) - \text{atan2}(L_2 \sin \theta_2, L_1 + L_2 \cos \theta_2) \quad (4)$$

Where:

- $\text{atan2}(y, x)$ : denotes the four-quadrant inverse tangent function, which enables an unambiguous determination of the rotation angle over the entire plane, in contrast to the conventional arctan function.
- $-y$ : This term results from the adopted vertical reference frame, where the positive y-axis is defined upward and therefore opposes the direction of the gravitational vector when the leg is in the fully extended posture.

## 2.2. Dynamics of the Two-Degree-of-Freedom Lower-Limb Exoskeleton

### 2.2.1. Lagrange Formulation

To achieve accurate trajectory tracking in controller design, the development of a dynamic model is a critical step, as it characterizes the relationship between joint torques and the resulting robot motion, including position, velocity, and acceleration.

The Lagrangian approach is based on the energy balance of the mechanical system. The Lagrangian function L is defined as the difference between the total kinetic energy K and the total potential energy P of the system:

$$\mathcal{L}(q, \dot{q}) = K(q, \dot{q}) - P(q) \quad (5)$$

Where:

- q: denotes the vector of joint variables (angular positions).
- $\dot{q}$ : represents the vector of joint velocities.
- K: is the total kinetic energy of the system.
- P: is the total potential energy of the system.

The general Lagrange–Euler dynamic equations are expressed as:

$$\frac{d}{dt} \left( \frac{\partial \mathcal{L}}{\partial \dot{q}_i} \right) - \frac{\partial \mathcal{L}}{\partial q_i} = \tau_i \quad (6)$$

Where:

- $\tau_i$ : denotes the control torque applied at the  $i$ -th joint.
- $i = 1, 2$  correspond to the hip and knee joints, respectively.

The differential equations of motion of the two-degree-of-freedom lower-limb exoskeleton can be compactly expressed in the following general matrix form:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + B\dot{q} = \tau \quad (7)$$

The elements of this formulation are derived from the geometric and mass properties of each link, where the associated matrices and vectors are given by:

$$M(q) = \begin{bmatrix} m_1 l_{c1}^2 + m_2 (l_1^2 + l_{c2}^2 + 2l_1 l_{c2} \cos \theta_2) + I_1 + I_2 & m_2 (l_{c2}^2 + l_1 l_{c2} \cos \theta_2) + I_2 \\ m_2 (l_{c2}^2 + l_1 l_{c2} \cos \theta_2) + I_2 & m_2 l_{c2}^2 + I_2 \end{bmatrix} \quad (8)$$

$$C(q, \dot{q}) = \begin{bmatrix} -m_2 l_1 l_{c2} \sin \theta_2 \dot{\theta}_2 & -m_2 l_1 l_{c2} \sin \theta_2 (\dot{\theta}_1 + \dot{\theta}_2) \\ m_2 l_1 l_{c2} \sin \theta_2 \dot{\theta}_1 & 0 \end{bmatrix} \quad (9)$$

$$G(q) = \begin{bmatrix} (m_1 l_{c1} + m_2 l_1)g \cos \theta_1 + m_2 l_{c2} g \cos(\theta_1 + \theta_2) \\ m_2 l_{c2} g \cos(\theta_1 + \theta_2) \end{bmatrix} \quad (10)$$

Where:

$q = [\theta_1 \ \theta_2]^T$  : denotes the vector of joint angular positions.

$\tau = [\tau_1 \ \tau_2]^T$  : represents the vector of control torques applied at the joints.

$M(q)$ : is the inertia matrix of the system.

$C(q, \dot{q})$ : Coriolis & Centrifugal Matrix

$G(q)$ : Gravity Vector

$B\dot{q}$  :accounts for viscous friction effects at the joints.

### III. CONTROL SYSTEM DESIGN

#### 3.1. PID Controller Integrated with Particle Swarm Optimization (PSO)

To enable the exoskeleton robot to accurately track biologically inspired human gait trajectories, the control system must effectively handle inherent nonlinearities as well as continuously varying load conditions during motion [3], [6], [14]. This section presents the design of a PID controller integrated with the PSO algorithm, which facilitates automatic parameter tuning and eliminates the reliance on conventional manual trial-and-error approaches[10], [12], [13].

##### 3.1.1. PID Controller

PID, standing for Proportional–Integral–Derivative, is a closed-loop feedback controller that combines proportional, integral, and derivative control actions[11]. This combination allows the controller to minimize tracking error, improve transient response speed, reduce overshoot, and suppress undesired oscillations[6],[11]. Owing to its simplicity, robustness, and ease of implementation, PID control has been extensively applied in modern industrial and robotic control systems[7], [11].

In this study, the conventional PID formulation is enhanced by incorporating a gravity compensation term  $G(q)$ , making it more suitable for the dynamic characteristics of the lower-limb exoskeleton [6],[9]. The complete PID control law with gravity compensation is expressed as follows:

$$\tau = K_p(q_d - q) + K_i \int (q_d - q) dt + K_d(\dot{q}_d - \dot{q}) + G(q) \quad (11)$$

In this study, the Ziegler–Nichols method is adopted to determine the controller parameters for subsequent analysis[8], [11].

**Table 2. PID parameter tuning rules based on the closed-loop Z–N method**

Controller	K <sub>p</sub>	T <sub>i</sub>	T <sub>d</sub>	K <sub>i</sub> =K <sub>p</sub> /T <sub>i</sub>	K <sub>d</sub> =K <sub>p</sub> .T <sub>d</sub>
P	0.5K <sub>u</sub>	-	-	-	-
PI	0.45K <sub>u</sub>	0.83T <sub>u</sub>	-	0.54K <sub>u</sub> /T <sub>u</sub>	-
PID	0.6K <sub>u</sub>	0.5T <sub>u</sub>	0.125T <sub>u</sub>	1.2K <sub>u</sub> /T <sub>u</sub>	0.075K <sub>u</sub> .T <sub>u</sub>

### 3.1.2. Particle Swarm Optimization (PSO) algorithm

Particle swarm optimization (PSO) is a population-based stochastic optimization technique inspired by the collective motion observed in natural swarms[10],[12], such as flocks of birds and schools of fish. This collective behavior motivated Kennedy and Eberhart to propose PSO as an efficient search method for solving complex optimization problems[10].

Fundamentally, PSO belongs to the class of swarm intelligence (SI) algorithms[10],[12]. Rather than performing an isolated search, PSO operates on a population of candidate solutions, referred to as particles, which are iteratively updated over successive generations. The optimization capability of PSO arises from the interaction among particles, whereby both individual experience and global information are shared within the swarm[10],[12] to guide the search process toward an optimal solution.

In this study, the PSO algorithm is employed to simultaneously search for the optimal parameter sets of the PID controllers for both the hip and knee joints [5],[10], [12].

- **Search space:** Each particle is represented by a six-dimensional vector (D=6), corresponding to the six control parameters of the hip and knee joint PID controllers:

$$X = [K_{p1}, K_{i1}, K_{d1}, K_{p2}, K_{i2}, K_{d2}]$$

- **Objective function:** To evaluate the quality of each candidate parameter set, the integral of time-weighted absolute error (ITAE) criterion is adopted as the objective function[12],[13]. The ITAE index penalizes errors that persist over time, thereby contributing to reduced settling time and improved steady-state accuracy[12],[13] of the control system.

$$J = \int_0^T t \cdot (|e_{\text{hip}}(t)| + |e_{\text{knee}}(t)|) dt \quad (12)$$

Where,  $e_{\text{hip}}(t)$  và  $e_{\text{knee}}(t)$  denote the instantaneous trajectory tracking errors of the hip and knee joints, respectively. The objective of the PSO algorithm is to determine the parameter vector  $X$  that minimizes the cost function  $J$ .

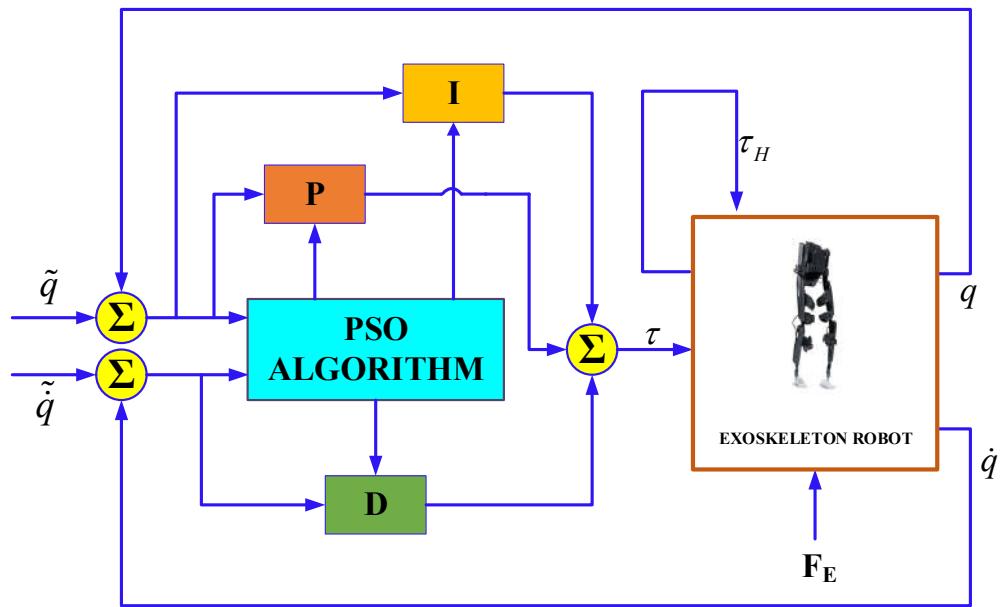


Fig. 2 The proposed PSO-based PID control structure

- ❖ The flowchart of the closed-loop Ziegler–Nichols method and PSO algorithm proposed in this work is shown in Fig. 3.

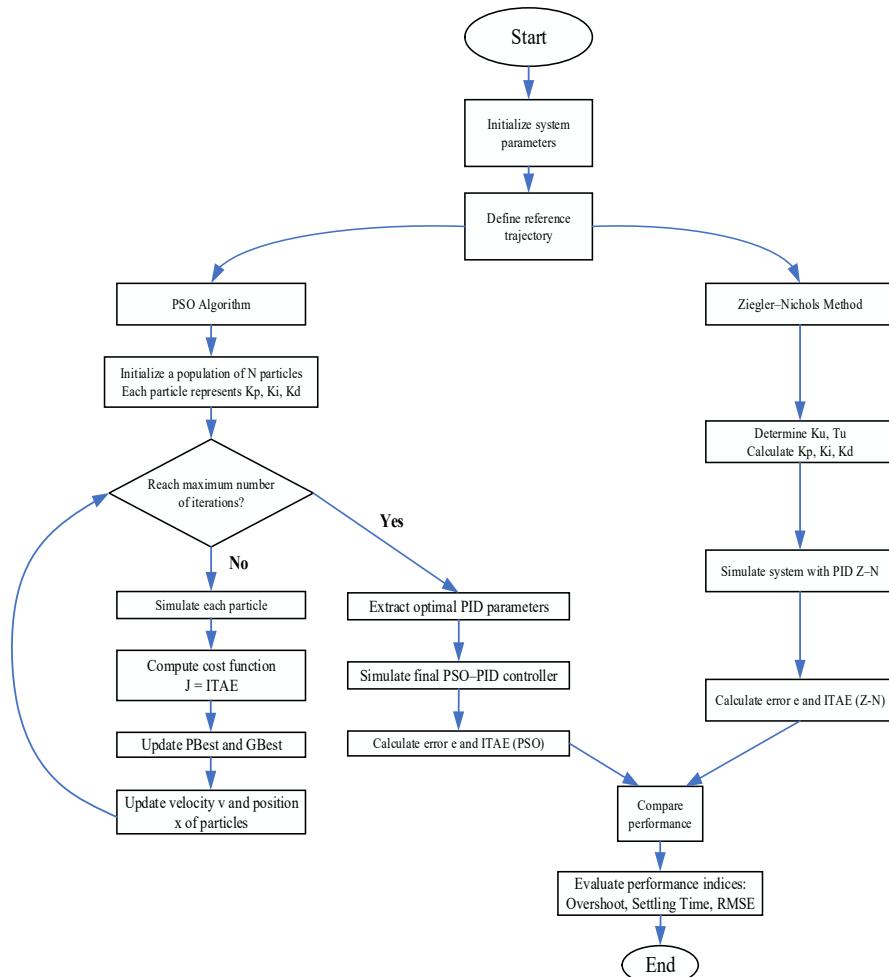


Fig. 3 The entire flowchart of for the proposed control system

#### IV. SIMULATION SETUP AND RESULTS

##### 4.1. PID controller design for the two-DOF exoskeleton robot

The entire simulation model built in Matlab/Simulink platform is illustrated in Fig. 4.

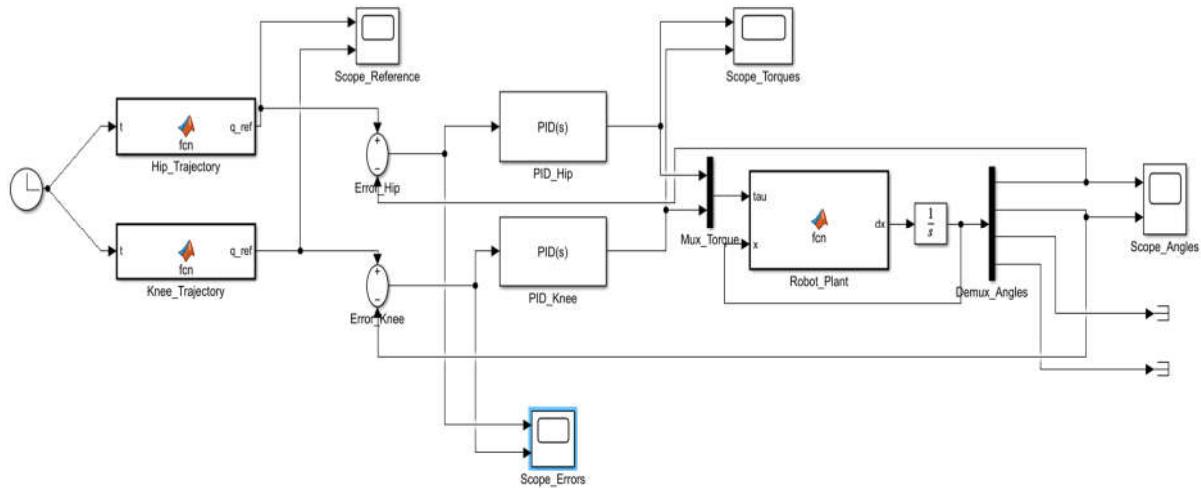


Fig. 4 MATLAB/Simulink simulation block diagram

The system parameters used for simulation are summarized in Table 3.

Table 3. Physical parameters of the two-DOF lower-limb exoskeleton

Symbol	Parameter description	Value	Unit
m1	Thigh segment mass	5	kg
m2	Shank segment mass	3	kg
l1	Thigh length	0.5	m
l2	Shank length	0.4	m
lc1	Distance from hip joint to thigh center of mass	0.25	m
lc2	Distance from knee joint to shank center of mass	0.2	m
j1	Thigh moment of inertia	0.4167	kg · m <sup>2</sup>
j2	Shank moment of inertia	0.16	kg · m <sup>2</sup>
b1	Hip joint viscous friction coefficient	0.02	N·m·s/rad
g	Gravitational acceleration	9.81	m/s <sup>2</sup>
b2	Knee joint viscous friction coefficient	0.01	N·m·s/rad

Table 4. Gait trajectory parameters and simulation settings

Symbol	Parameter description	Value	Unit
f_gait	Gait frequency	0.83	Hz
A_hip	Hip joint angular amplitude	0.35	rad
θ_offset	Hip joint offset angle	0.1	rad

A_knee	Knee joint angular amplitude	0.5	rad
-	Total simulation duration	6	s
-	Initial state (position, velocity)	[0, 0, 0, 0]	-

#### 4.2. Simulation Results

The simulation results obtained in MATLAB/Simulink are illustrated in Figs. 5-8. Also, Table 5 represents analysis on these simulation results. They verify that the proposed control method is one of the best choices for the exoskeleton robot's control.

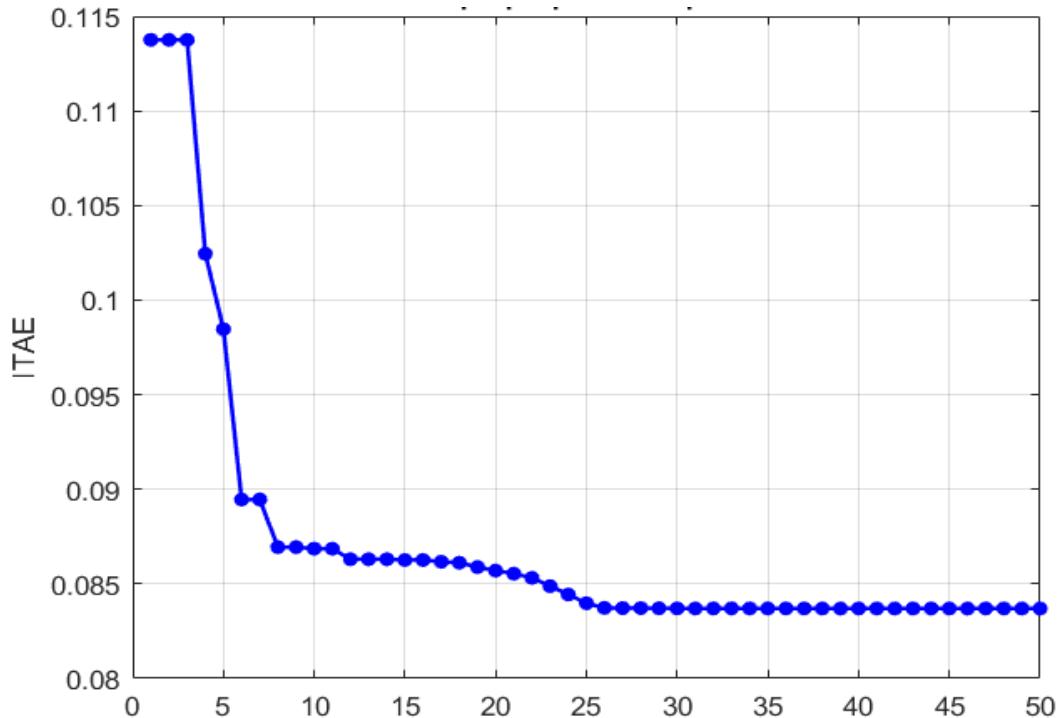
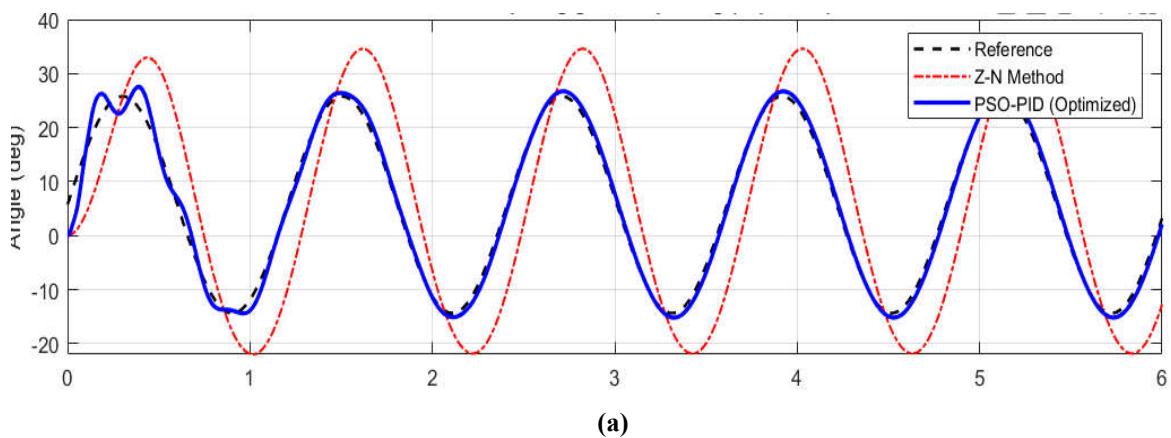


Fig. 5 Convergence behavior of the PSO algorithm



(a)

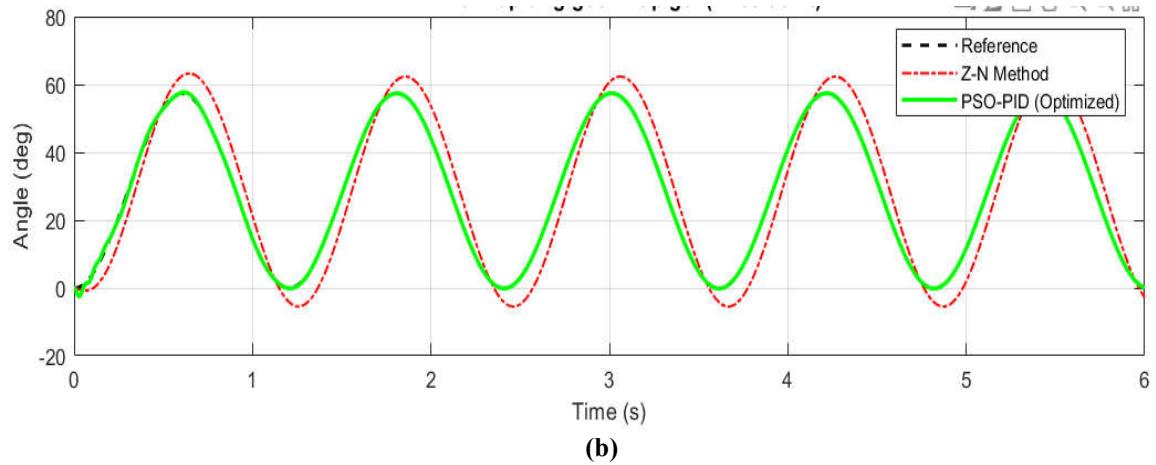


Fig. 6 Angular responses of the hip and knee joints during gait tracking

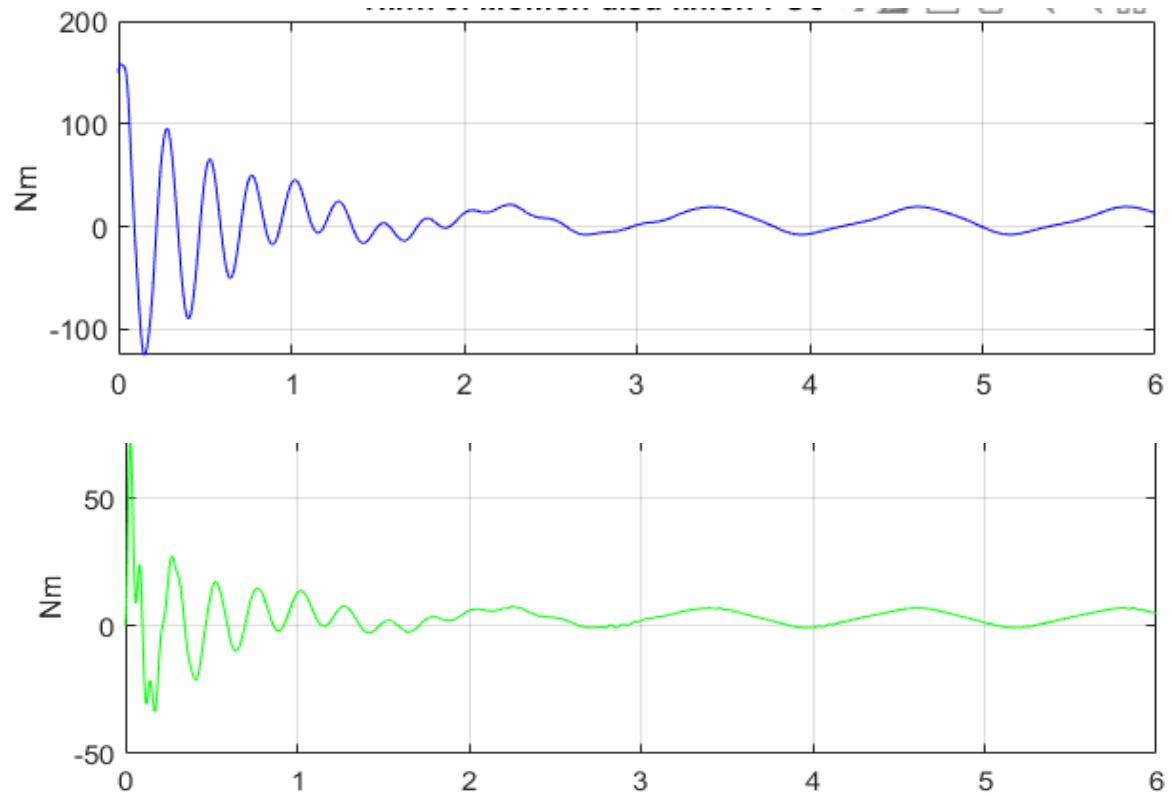
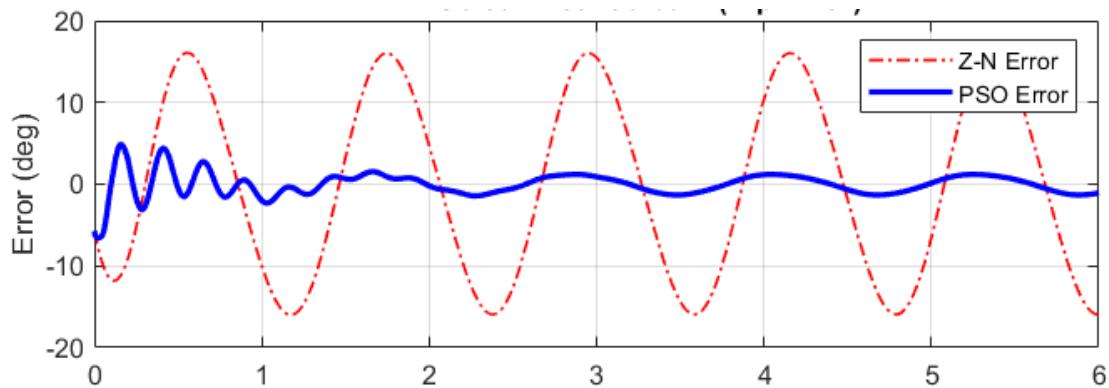


Fig. 7 PSO-based control torques at the hip and knee joints



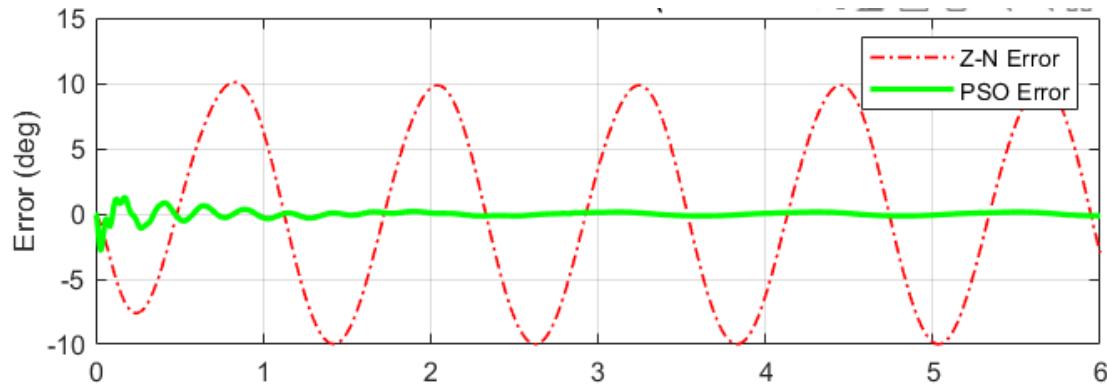


Fig. 8 Comparison of hip and knee joint tracking errors

Remarks and performance evaluation:

Table 5. Controller performance evaluation criteria

Evaluation Criterion	Ziegler-Nichols (Z-N) method	PSO-PID method	Performance Assessment
1. Trajectory Tracking	Poor. The output response exhibits strong oscillations, noticeable phase lag, and large amplitude deviations relative to the reference signal.	High. The output response closely follows the reference signal and is almost coincident with the desired trajectory.	PSO-PID effectively eliminates phase and amplitude deviations compared with the Z-N method.
2. Tracking Error	Large. The tracking error remains sinusoidal with considerable amplitude: - Hip joint: $\sim \pm 15^\circ$ - Knee joint: $\sim \pm 10^\circ$	Very small. The error converges rapidly to zero and remains negligible after the transient phase.	PSO-PID significantly reduces tracking error, ensuring high positioning accuracy.
3. Overshoot	High. The output frequently exceeds the reference trajectory, inducing undesirable oscillations.	Low / negligible. The output response is smooth, with no significant overshoot that could compromise stability.	PSO-PID enhances operational safety and avoids abrupt motions.
4. Settling Time	Prolonged. The system struggles to reach steady state, with persistent oscillations over time.	Short. The error decreases rapidly from the initial moment and remains stable throughout the simulation period.	PSO-PID achieves faster system response and reduced transient duration.
5. ITAE index	Not optimized with respect to ITAE	Optimized. The ITAE value converges rapidly and reaches a minimum of approximately 0.084 after about 25 generations.	PSO successfully identifies a well-balanced parameter set between response speed and accuracy.
6.(Control Input/Torque)	Poor stability, with large oscillations inferred from the oscillatory output response.	Smooth. The control torque varies in a physically reasonable manner and	Contributes to energy efficiency and extends actuator lifespan.

Evaluation Criterion	Ziegler-Nichols (Z-N) method	PSO-PID method	Performance Assessment
		suppresses oscillations shortly after startup.	

## V. CONCLUSIONS

This study addressed the trajectory-tracking control problem of a two-degree-of-freedom lower-limb exoskeleton robot, a system of significant relevance in rehabilitation and assistive applications. Based on a rigorous Lagrangian dynamic formulation to capture the nonlinear characteristics of the system, an optimized PID control strategy tuned using the PSO algorithm was proposed and systematically evaluated.

A key contribution of this work lies in the adoption of the Integral of Time-weighted Absolute Error (ITAE) as the objective function for PSO-based parameter optimization. This choice effectively overcomes the inherent limitations of conventional tuning approaches, such as the Ziegler–Nichols method or manual trial-and-error techniques, which are highly dependent on empirical experience and often fail to achieve an adequate balance between stability and response speed. Simulation results obtained in the MATLAB/Simulink environment provide convincing quantitative evidence of the superiority of the proposed approach.

Specifically, the PSO-tuned PID controller demonstrated markedly improved trajectory-tracking performance compared with the Ziegler–Nichols (Z–N) method. While the Z–N-based controller exhibited large tracking errors, characterized by oscillation amplitudes of approximately  $\pm 15^\circ$  at the hip joint and  $\pm 10^\circ$  at the knee joint, along with significant overshoot, the PSO–PID controller-maintained errors close to zero and almost completely eliminated overshoots. In addition, the system settling time was substantially reduced, enabling smooth and stable robot operation shortly after the startup phase. Notably, the control torque profiles generated by the PSO–PID controller exhibited smooth and physically reasonable variations without extreme oscillations, which is particularly important for ensuring user safety and prolonging actuator lifespan.

In summary, the findings confirm that integrating Particle Swarm Optimization with a PID controller constitutes an effective and practical approach for enhancing control performance in complex biomedical robotic systems. The results obtained from this study provide a solid scientific foundation for future experimental validation on physical prototypes, as well as for extending the model to three-dimensional motion and incorporating biological signals such as electromyography (EMG) to further improve human–robot interaction in subsequent research.

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