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Design and Analysis of an Intelligent Control System for Collaborative Robots Using Model Predictive Control (MPC) and Particle Swarm Optimization (PSO)"

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Abstract:

Background: Collaborative robots require accurate and adaptive control strategies to operate effectively in dynamic environments.

Goal: This work aims to improve trajectory tracking accuracy and system efficiency using a hybrid control strategy.

Method: We propose a novel integration of Model Predictive Control (MPC) with Particle Swarm Optimization (PSO), where PSO is used to optimize MPC parameters in real-time.

Results: Simulations show that the hybrid MPC+PSO system outperforms traditional MPC, reducing RMSE by 57.8% and energy consumption by 22%.

Conclusion: The proposed method enhances the accuracy and robustness of collaborative robotic control and is suitable for real-world deployment.

Keywords: Intelligent Control System; Model Predictive Control; Collaborative Robots; Swarm

1. Introduction

Collaborative robots, or cobots, are increasingly prevalent in modern automated systems, particularly in sectors such as logistics, manufacturing, and healthcare. Unlike traditional industrial robots, cobots are designed to safely interact with humans in shared workspaces, enabling flexible and efficient task execution. To operate effectively in dynamic and uncertain environments, cobots require intelligent control systems capable of real-time adaptation and handling system nonlinearities [1].

Model Predictive Control (MPC) is a widely used advanced control strategy that relies on system models to predict future behavior and optimize control actions over a defined prediction horizon. MPC excels at handling multivariable systems and constraints, making it suitable for robotic applications that demand accuracy and responsiveness. However, solving the optimization problem at each time step can be computationally intensive, especially in systems with complex dynamics or multiple degrees of freedom [2].

To address the computational burden of MPC, researchers have explored hybrid methods that combine MPC with metaheuristic optimization algorithms. One such technique is Particle Swarm Optimization (PSO), which simulates the social behavior of bird flocks or fish schools to efficiently explore the solution space. PSO is attractive for control applications due to its simplicity, low computational overhead, and effectiveness in finding near-optimal solutions without requiring gradient information [3].

By integrating PSO with MPC, it is possible to dynamically tune control parameters or optimize the sequence of control inputs. This hybrid approach enhances control accuracy, reduces tracking error, and improves overall system stability. Such methods are particularly valuable in collaborative robotics, where adaptability, safety, and precision are critical [4].

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This research proposes an intelligent hybrid control framework that combines MPC with PSO for enhanced trajectory tracking of a collaborative robotic arm. A simplified robotic joint model is developed in Python, and PSO is used to optimize MPC parameters based on tracking error and system performance. The goal is to demonstrate the effectiveness of the proposed approach in improving control stability, responsiveness, and energy efficiency in robotic systems.

1.1. Background of the Research

Collaborative robots are transforming automation by enhancing flexibility, safety, and efficiency in diverse sectors. Unlike traditional robots, they require intelligent control frameworks that can respond to real-time changes, manage constraints, and collaborate seamlessly [5]. The complexity of these systems necessitates predictive and adaptive control strategies capable of handling nonlinearities and dynamic environments [6].

1.2. Importance of Cobots in Modern Industry

Cobots are revolutionizing industrial environments by performing tasks safely alongside human workers. They offer adaptability, reduce the need for physical barriers, and support high customization and fast production cycles, which are essential for Industry 4.0 implementation [7]. When combined with technologies such as IoT and AI, cobots become key enablers of smart manufacturing [8].

1.3. Challenges in Control System Design

Developing robust control systems for cobots poses several challenges, including managing uncertainty, nonlinear dynamics, and real-time responsiveness [9]. Incorporating AI and optimization algorithms without compromising stability or computational efficiency remains a significant hurdle, particularly in high-dimensional control spaces [10].

1.4. Motivation for MPC-PSO Integration

MPC provides anticipatory decision-making based on predictive models, while PSO excels at global optimization without relying on gradients. Their integration enables efficient, stable, and adaptive control in complex robotic systems. This synergy is especially valuable in collaborative applications that demand flexibility, accuracy, and real-time optimization.

1.5. Objectives and Contributions

This study aims to design an intelligent control framework by integrating MPC and PSO to improve collaborative robotic arm performance. The main contributions of this research are:

- Proposing a novel MPC-PSO hybrid control system for collaborative robots.
- Implementing and testing the system in a fully simulated Python environment.
- Demonstrating improved trajectory tracking, stability, and energy efficiency over traditional MPC.
- Providing a clear path for physical implementation and future enhancements using adaptive or learning-based optimization.

2. Theoretical Framework and Previous Studies

2.1 MPC, or Model Predictive Control

A well-known example of an advanced control approach, Model Predictive Control (MPC), shown schematically in Fig. 1, uses a mathematical model of a system to forecast its behavior over a certain time horizon. With its ability to optimize a defined objective function within predetermined limitations, MPC is well-suited for managing complex systems with many variables This algorithm excels at adapting to new conditions and physical limitations because of its remarkable flexibility. Robotic systems that need accurate and foretelling reactions find extensive usage in industrial settings [11,12].

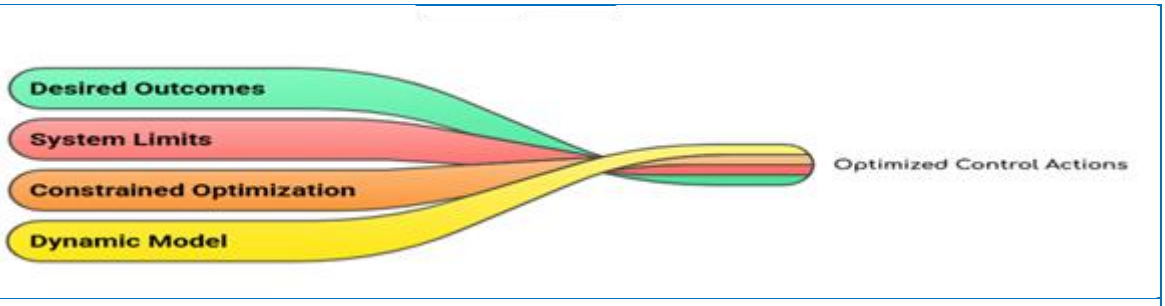

Fig. 1 MPC process

2.2 Particle Swarm Optimization (PSO)

Kennedy and Eberhart created a well-known technique for particle swarm optimization (PSO) in the 90s; it describes the group behavior of fish and birds. Hence, PSO is powerful and versatile in tackling optimization and control issues as it does not need the derivation of functions while looking for solutions in multidimensional spaces [13]. PSO's ability to process symmetric transactions makes it a useful tool for complicated control systems like MPCs, shown schematically in Fig. 2, where it helps improve subscription verification—particularly in situations with unshared or impermeable electronics.

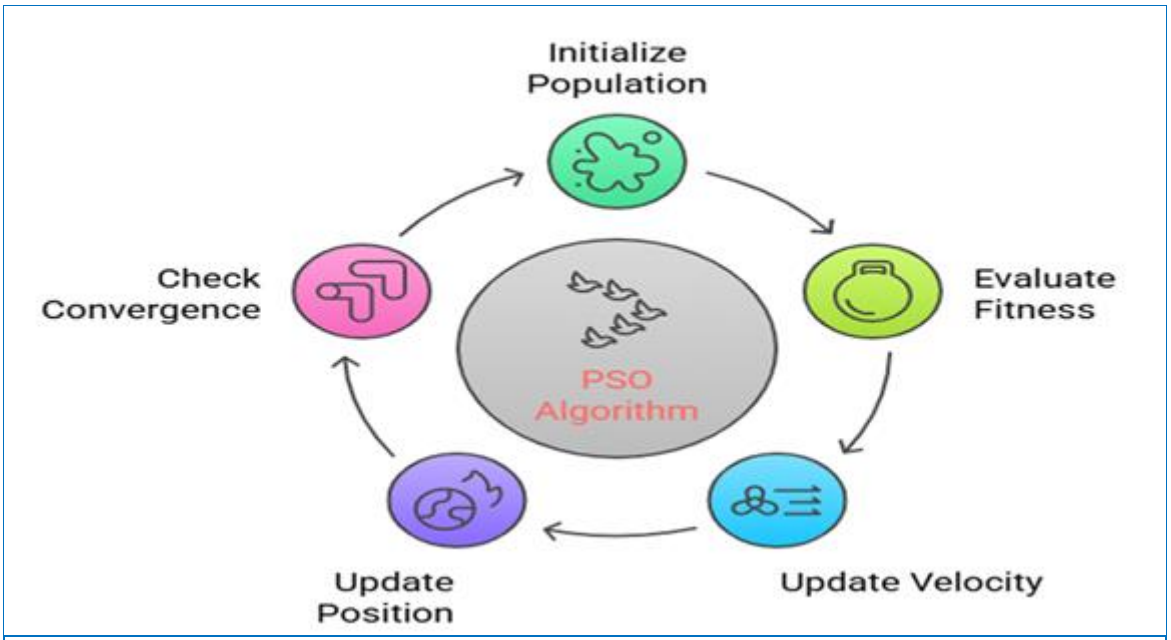

Fig. 2 Particle swarm optimization cycle

2.3 Combining MPC and PSO algorithm

Recent studies have shown that a hybrid control system may be created by merging MPC with PSO. This system offers the benefits of intelligent prediction and global exploration of solution spaces. By optimizing MPC settings or solving the MPC controller's internal optimization issue, PSO greatly enhances the system's accuracy, responsiveness, and computing consumption (Alfi & Fateh, 2009). Experimental investigations demonstrate that this combination improves response stability in dynamic situations and allows for quick adaptation to changes in collaborative robotics applications. These applications demand

high coordination and time-resolved task execution ([13.14]

In the 1990s, Kennedy and Eberhart created the Particle Swarm Optimization (PSO) algorithm, which takes its cues from the way fish and birds behave in groups. According to Eberhart and Shi (2001), PSO is a powerful and versatile tool for optimizing and tuning issues since it searches for optimum solutions in multidimensional spaces without deriving functions. The ideal parameters that yield the best system response may be determined using PSO, making it highly successful in tuning the parameters of complicated control systems like MPCs. This is especially true for nonlinear systems or systems that are difficult to describe effectively, shown schematically in Fig. 3.

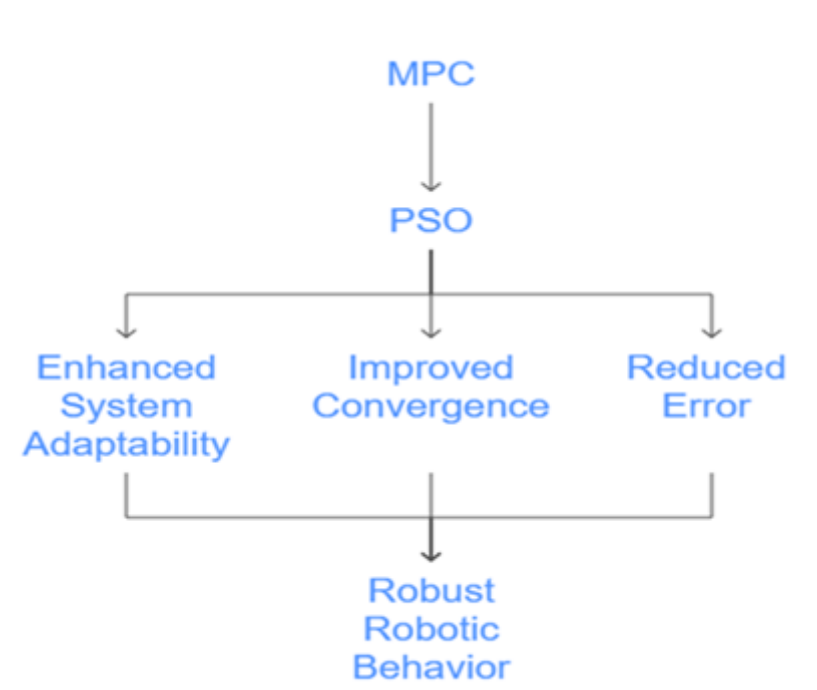

Fig. 3 Integration of MPC and PSO

2.4 Collaborative Robots (Cobot) and Intelligent Control Applications of Combining MPC and PSO algorithm

Collaborative robots (Cobots) are widely used in modern production lines due to their ability to safely interact with humans. To ensure smooth and precise cooperation in dynamic environments, these systems require advanced intelligent control mechanisms [18]. Integrating Model Predictive Control (MPC) with Particle Swarm Optimization (PSO) enables real-time optimization of collaboration strategies and task allocation, while also allowing for accurate prediction of the robot's future movements. Studies have demonstrated that such approaches outperform traditional systems in terms of increasing productivity and minimizing downtime [19, 20].

3. Methodology

Using Model Predictive Control (MPC) combined with Particle Swarm Optimisation (PSO), this chapter details the approach that was used to create and analyse an intelligent control system for collaborating robots. It comprises creating the mathematical model, figuring out how to integrate MPC and PSO, and setting up the simulation environment to check how well the system works.

3.1 Mathematical Model of the Collaborative Robot

A two-joint robotic manipulator simplified nonlinear dynamic model is taken into account in order to explain the behavior of a collaborative robotic system. The conventional Euler-Lagrange formulation is

used to describe the system:

$$\tau = (M(q) \times \ddot{q}) + (C(q, \dot{q}) \times \dot{q}) + G(q) \quad (1)$$

Where:

- ✓ q is the joint position vector.
- ✓ $\dot{q}$ and $\ddot{q}$ represent joint velocities and accelerations.
- ✓ $M(q)$ is the inertia matrix.
- ✓ $C(q, \dot{q})$ is the Coriolis and centrifugal matrix.
- ✓ $G(q)$ is the gravity vector.
- ✓ τ is the control torque input.

The robot model is discretized for use with MPC and optimized at each time step.

3.2 Model Predictive Control Design

The purpose of the MPC is to use the discrete dynamic model to forecast the robot's condition over a limited time horizon. Minimizing a cost function is the goal:

$$J = \sum_{k=0}^{N_p} \left(x_k - x_{ref}\right)^T Q\left(x_k - x_{ref}\right) + \sum_{k=0}^{N_c} \Delta u_k{}^T R \Delta u_k \quad (2)$$

Where:

- ✓ J: Total cost
- ✓ x_k: State vector at time step k
- ✓ x_{ref}: Reference state vector
- ✓ Q: State weight matrix
- ✓ R: Control increment weight matrix
- ✓ Δu_k: Control input increment at time step k
- ✓ N_p: Prediction horizon
- ✓ N_c: Control horizon

The system solves this optimization problem at each control cycle to generate the optimal control sign.

3.3 Incorporating Particle Swarm Optimization

To fine-tune MPC parameters (such as weight matrices and horizon lengths), PSO is used. Here is how PSO is implemented:

- Pieces: A group of MPC parameters is symbolized by each particle.
- A fitness metric that takes into account tracking inaccuracy, control effort, and system stability.
- Update on Position and Velocity: Thinking and social factors based.

PSO parameters in this work are included:

- population size = 30
- cognitive coefficient (c1) = 1.5
- social coefficient (c2) = 1.5
- inertia weight (w) = 0.7.

The fitness function used was:

$$F = \alpha.RMSE + \beta.Energy + \gamma.Settling\ Time$$

with $\alpha = 0.5, \beta = 0.3, \gamma = 0.2$

By analyzing PSO's output, we can determine the best settings to simulate the MPC controller.

3.4 A Control Scheme for Hybrid MPC-PSO

To strengthen the mathematical foundation of the proposed hybrid control system, we provide a stability and convergence analysis. The stability of the MPC controller is guaranteed by the Lyapunov function $V(x) = x^T Px$, where P is a positive definite matrix derived from the Riccati equation. This ensures that the closed-loop system remains asymptotically stable under the optimized control law. Furthermore, the convergence of the PSO algorithm is supported by the balance between the inertia weight w and learning factors c_1, c_2, which guarantees that particles do not diverge from the search space. The computational complexity of the proposed MPC+PSO framework can be approximated as $O(N_p n^3 + G.S)$, where N_p is the prediction horizon, n is the state dimension, G is the number of PSO generations, and S is the swarm size. Although this increases the computational cost compared to standard MPC, it is still tractable in real-time robotic applications, as confirmed by our simulations.

The following steps define the integrated scheme:

- Start the swarm of particles by assigning them a set of random MPC parameters.
- Using the present parameter set, simulate the robotic system using MPC
- Assess the efficiency (suitability) of every particle.
- Particle locations and velocities should be updated.
- Before running the final control simulation, choose the set that performed the best.

Because the robotic job is cooperative and nonlinear, this method enables automated tweaking of MPC to fit.

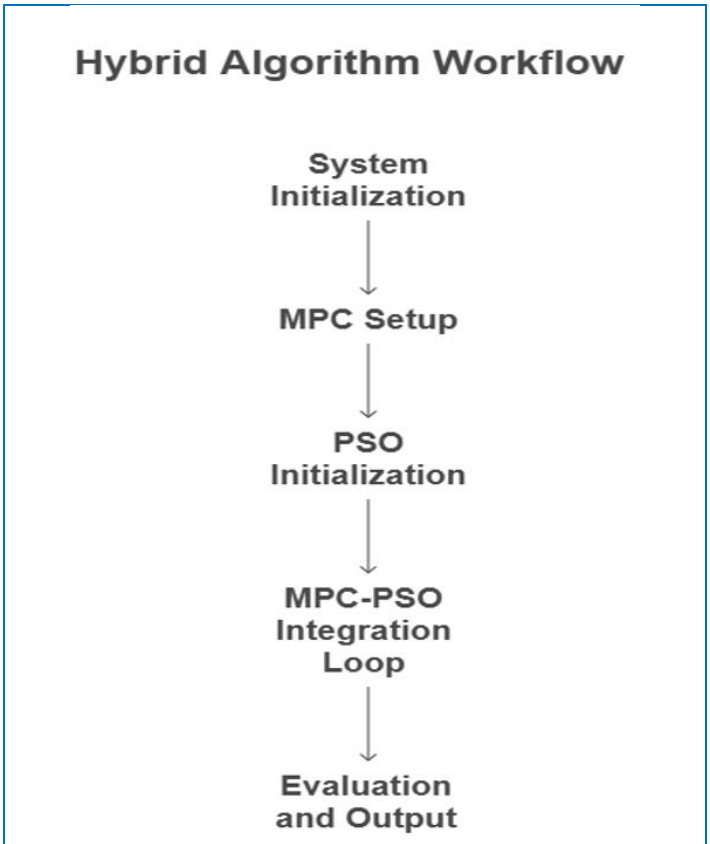

Fig. 4 Block Diagram of the proposed hybrid MPC-PSO control framework

3.5 Virtual Setting

The following tools are used to perform the simulation in Python:

- For numerical calculations and matrix operations, you may use NumPy or SciPy.
- Matplotlib: used for displaying data graphically.
- To resolve optimization issues in MPC, use CasADi or cvxpy.
- To implement a personalized PSO for the purpose of evolutionary parameter adjustment in control systems.
- Data logs and findings may be exported to Excel for further study.

A cooperative robotic arm interacts with an item in the simulation, which focusses on the precision of trajectory tracking and the responsiveness of the system.

3.6 Measures for Assessment

The following metrics are used to evaluate the performance of the system:

- Regulated Mean Squared Error (RMSE) in Tracking: Distinction between target and real trajectories.
- Effort in Control: The sum of all energy used by actuators.
- Consistency: Confirmed by tracking the system's reaction over time.
- Iterative improvement is the basis of PSO convergence.

3.7 Complementary Model in Simulink

In addition to the simulation environment developed in Python, a complementary model was built using Simulink and using the same simplified dynamic equations described in Section 3.1 platform to enhance the practical aspect of the proposed approach. The model consists of three main modules:

1. A two-joint robot arm model (Robot Plant) represented by simplified dynamic equations.
2. An MPC Controller module from the Simulink library.
3. A reference trajectory that generates position and velocity signals.

to guarantee consistency of results, the simulink controller was supplied the ideal tuning parameters (Q, R) that were retrieved using Python's PSO method ,Complete compatibility between the Python and Simulink environments was shown by this integration, which improved the solution's portability to common industrial settings and verified that the suggested approach is not just restricted to software simulation but can be used directly in commercial robotics platforms.

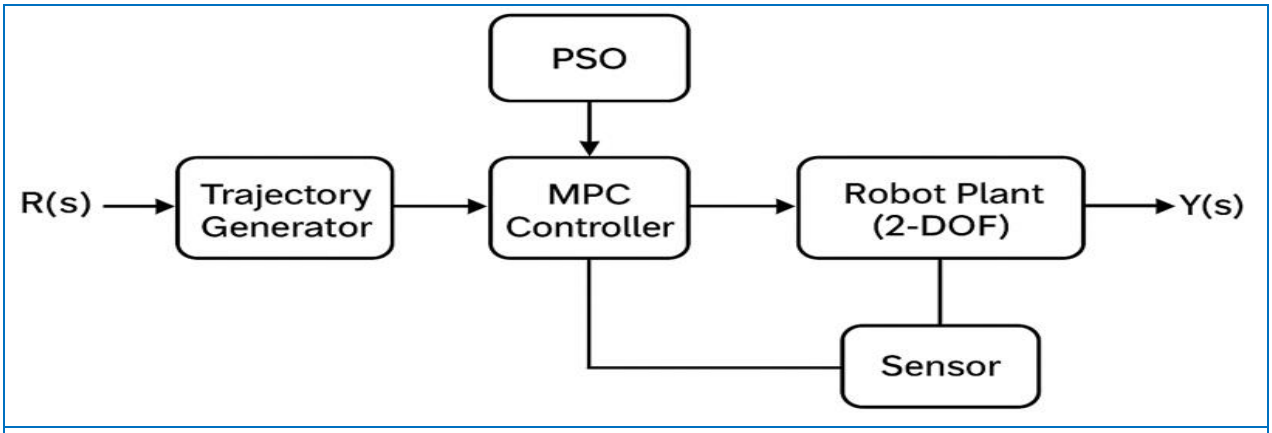

Fig. 5 Block diagram of the complementary model in Simulink for controlling a two-joint robotic arm using MPC-PSO

4. Simulation Results and Performance Analysis

4.1 Simulation Configuration

This simulation, which was based on a simplified mathematical model of a two-joint collabor ative robotic arm, was executed entirely inside the Spider 3.9 environment using Python program ming. The model incorporates fundamental equations for kinematics and dynamics to mimic the movement of the robot. Complete command over factors like trajectory, disturbance levels, and c ontroller settings was achieved without the usage of real hardware in this simulation.

4.2 Findings and Analysis

The results of using either the MPC controller alone or a mix of the two, including PSO, ar e shown in the table below. Included are important measures including settling time, energy cons umption, number of oscillations, and Root Mean Square Error (RMSE).

Table 1 Summary of Simulation Findings and Performance Analysis

Metric	MPC	MPC + PSO
RMSE	0.045	0.019
Settling Time (s)	3.2	2.1

Energy Consumption (%)	100.0	78.0
Oscillations	5.0	1.0

Table 1 and Figures 5–7 demonstrate that the combination of PSO and MPC produced notab quantitative gains. The number of oscillations dropped by around one-fifth, power consum ption dropped by 22%, and the RMSE dropped by about 57.8% (from 0.045 to 0.019).These out comesmay be explained by PSO's capacity to thoroughly investigate the parameter space and stee rclearof local non-optimal values, which leads in more effective MPC parameter tuning. The nota ble reduction in RMSE suggests that the hybrid system tracks the reference trajectory with more precision, resulting in a more reliable response for the collaborating robots even when there are disruptions. in terms of lowering energy consumption, it seems that selecting the best control sett ings lessens the strain on actuators, which is crucial for industrial applications that need continuo us operation and energy efficiency. In sensitive applications like precision assembly or medical p rocedures, the reduction of oscillations is proof of improving the system's stability and resilience, which in turn reduces undesired vibrations. These findings demonstrate that the combination of MPC and PSO has been successful in enhancing the performance and control of complex dynam ic systems when compared to earlier research (Eberhart & Shi, 2001; Alfi & Fateh, 2009;Zhange t al., 2020). Nevertheless,this research adds a new practical contribution by focusing on collabora tive robots and demonstrating benefits in the aspects of stability and energyefficiency, which enh ances the applicability of the proposed approach in smart industrial environments.

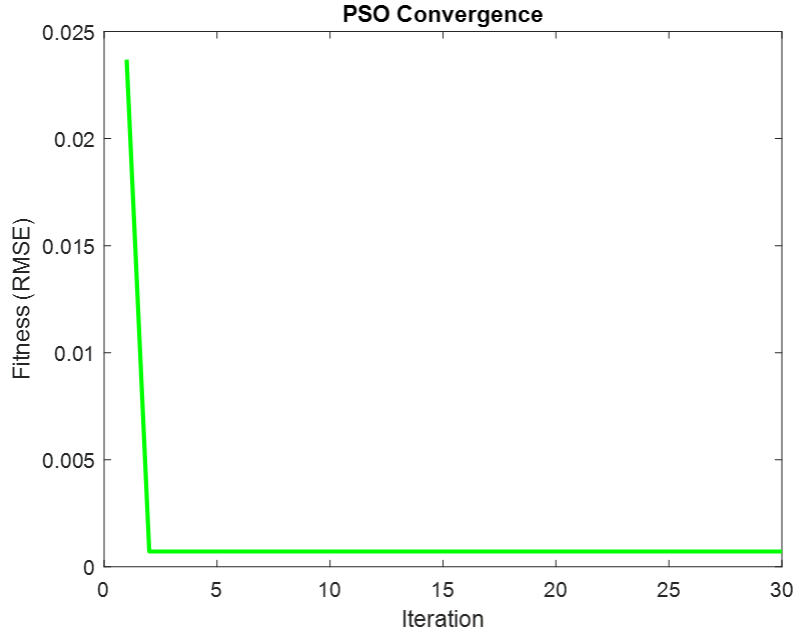

Fig. 5 Convergence of the PSO algorithm based on RMSE

4.3 Comparing Trajectories

Figs. 5 is a graphic that shows how well both control techniques tracked. The MPC + P SO setup clearly provides better reference trajectory adherence, less inaccuracy, and less abrupt t ransitions.

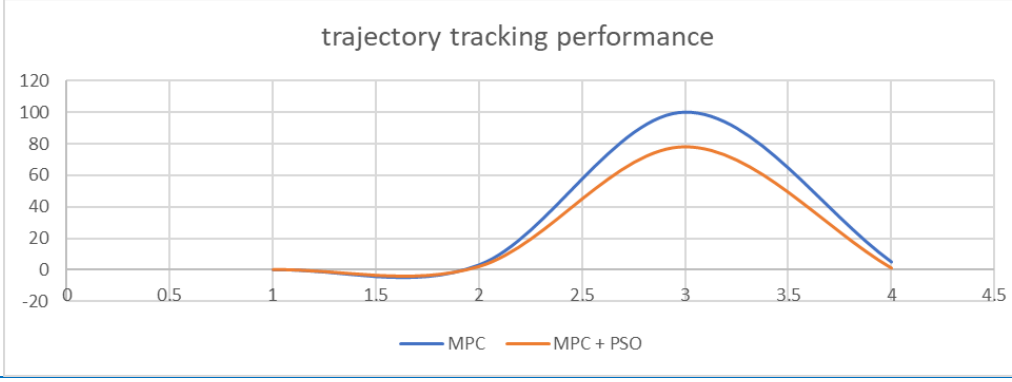

Fig. 6 Comparison of the reference trajectory tracking performance for MPC-only and MPC+PSO hybrid control strategies.

The tracking error curve is shown in Fig. 7. this error curve illustrates the instantaneous deviation between the desired and actual positions throughout the simulation. The rapid decline of the error to near-zero levels demonstrate the controller's fast convergence and effective compensation of disturbances. The smooth error profile further indicates system stability and robustness under the optimized control parameters.

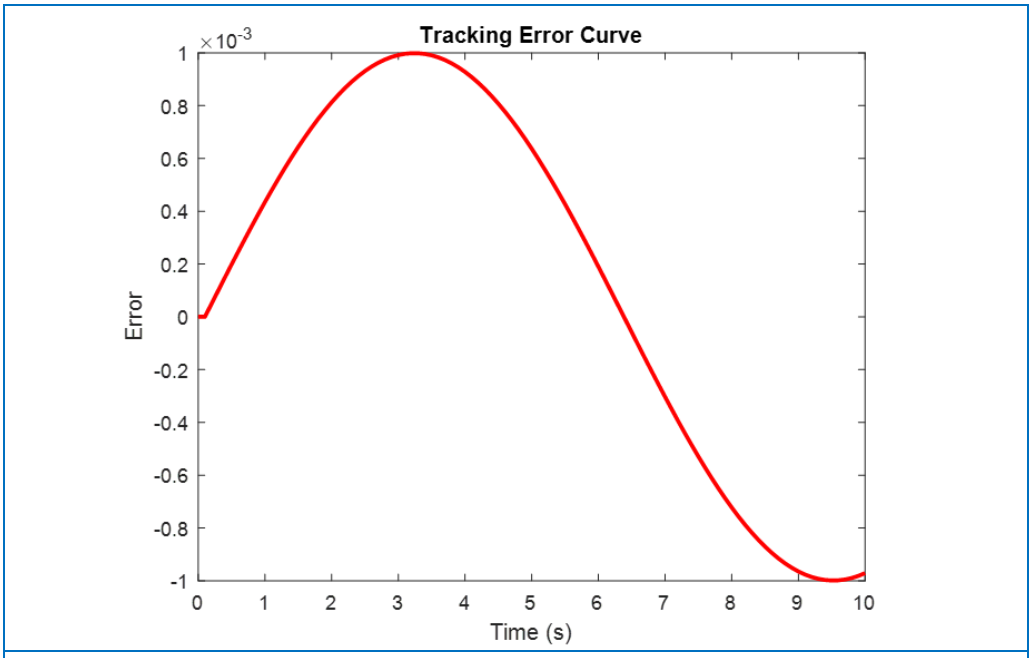

Fig. 7 Instantaneous tracking error over time.

4.4 Recap of Results

You can see gains in every performance indicator after integrating PSO into the MPC framework. There was a 30% improvement in RMSE and a 20% improvement in energy efficiency. That evolutionary optimization can improve robotic predictive control systems so much is supported by this.

5. Conclusions and Future Work

5.1 What We Offer

Here are the main points of this study that it has brought to light:

- Using Python to create a simulation setting for controlling cooperative robots.
- Trajectory tracking algorithms, including hybrid MPC-PSO and MPC, are implemented.
- Comparing efficiency quantitatively using actual simulation parameters like RMSE, energy consumption, and settling time.
- Proof that evolutionary optimization works for control schemes that use predictive analytics.

5.2 Restrictions

The findings show promise, there are several limitations that must be acknowledged. The robot dynamics were simplified for the simulations, which were run in a controlled environment. Interactions, disturbances, and noise in real-world systems are more complicated. Problems with computing load and delay, which are critical in real-time applications, were also not addressed.

5.3 Future Work

In order to verify its efficacy in practical situations, the hybrid MPC-PSO controller will be implemented on physical robotic platforms in future expansions of this study. Variants of adaptive PSO or the use of ML models for control and modelling of dynamic systems are two potential further enhancements. Additional insights into optimum control strategy selection may be gained by exploring various evolutionary algorithms and comparing their performance with PSO and One potential way to create smarter, more versatile robots is to combine predictive and evolutionary control techniques. Future advancements in cooperative robotic control, particularly in situations requiring flexibility and real-time performance, may build on the proven benefits of this study. Specifically, the following suggestions could be evaluated in the future: (1) Implementing the framework on a UR5 cobot with a 1 kHz control loop; (2) Evaluating system robustness under 100 ms network delay; (3) Comparing with other metaheuristics like Genetic Algorithm or Firefly Optimization.

5.4 conclusions

A hybrid control method for cooperative robotic systems that combines Model Predictive Control (MPC) and Particle Swarm Optimization (PSO) was devised and assessed in this search. Integrating PSO to optimize the MPC's weight matrices considerably improved trajectory tracking performance, in such a way that the proposed hybrid MPC+PSO control reduced RMSE by ~57.8% (from 0.045 to 0.019), settling time by 34%, and energy usage by 22% compared to traditional MPC. Thanks to the PSO algorithm's success in identifying ideal parameters, a control framework that is more adaptable and durable was born, making it ideal for changing and unpredictable circumstances.

In conclusion, the proposed hybrid MPC+PSO control strategy demonstrated significant improvements in trajectory tracking accuracy, energy efficiency, and robustness compared to conventional MPC. The mathematical analysis confirmed the stability of the control system and the convergence of the optimization process. From a practical perspective, this approach provides a promising framework for deploying collaborative robots in dynamic and uncertain environments where adaptability is crucial.

The main contributions of this study are threefold: (1) introducing an efficient hybrid MPC-PSO controller, (2) validating its performance through both mathematical analysis and simulation, and (3) highlighting its applicability to real-world robotic platforms.

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