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Article

A Hybrid PSO-ACO Algorithm for Precise Localization and Geometric Error Reduction in Industrial Robots

Ghulam E Mustafa Abro[1*], Eman Mahmoud[2]

[1] Interdisciplinary Research Centre for Aviation and Space Exploration, King Fahd University of Petroleum and Minerals (KFUPM), Dhahran 31261, Saudi Arabia

[2] Aerospace Engineering Department, King Fahd University of Petroleum and Minerals (KFUPM), Dhahran 31261, Saudi Arabia

[*] Corresponding email: Ghulam E Mustafa Abro (Mustafa.abro@ieee.org)

Abstract: The proposed hybrid optimization algorithm integrates particle swarm optimizatio (PSO) with Ant Colony Optimization (ACO) to improve a number of pitfalls within PSO methods traditionally considered and/or applied to industrial robots. Particle Swarm Optimization may frequently suffer from local optima and inaccuracies in identifying the geometric parameters, which are necessary for applications requiring high-accuracy performances. The proposed approach integrates pheromone-based learning of ACO with the D-H method of developing an error model; hence, the global search effectiveness together with the convergence accuracy is further improved. Comparison studies of the hybrid PSO-ACO algorithm show higher precision and effectiveness in the optimization of geometric error parameters compared to the traditional methods. This is a remarkable reduction of localization errors, thus yielding accuracy and reliability in industrial robotic systems, as the results show. This approach improves performance in those applications that demand high geometric calibration by reducing the geometric error. The paper provides an overview of input for developing robotics and automation, giving importance to precision in industrial engineering. The proposed hybrid methodology is a good way to enhance the working accuracy and effectiveness of industrial robots and shall enable their wide application to complex tasks that require a high degree of accuracy.

Keywords: particle swarm optimization; local optima; denavit-hartenberg; ant colony optimization and geometric error

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1 Introduction

Geometric parameter errors have a substantial impact on the positioning accuracy of industrial robotics, with a primary cause of localization errors being the deformation of connecting rods[1,2]. The compensation for these errors typically entails parameter identification, correction, data acquisition, and error modeling. The Denavit-Hartenberg (D-H) and Modified D-H (MDH) frameworks are among the most frequently employed models for error modeling in robotics[3]. Accurate parameter identification is the primary obstacle in error compensation, and numerous researchers have investigated a variety of optimization strategies to improve precision. This issue has been addressed through the development of numerous algorithms. Marquardt et al. introduced the Levenberg-Marquardt (L-M) algorithm to estimate robot error parameters. However, its accuracy is restricted by its iteration inefficiency and dependence on initial parameter selection[4].

Fang Lijin et al. implemented a quantum particle swarm algorithm to compensate for robotic errors;

however, its computational complexity renders it unsuitable for engineering applications[5]. Robert et al. investigated a simulated annealing algorithm; however, its efficiency was diminished by its lengthy iteration periods and slow convergence[6]. In the meantime, Zhong et al. implemented neural networks to mitigate localization errors in PUMA robots. However, this method necessitates a substantial quantity of training data and substantial computational resources, rendering real-time applications difficult[7]. While these methods have their advantages, they also have significant drawbacks when it comes to resolving industrial robot localization errors. The prevalence of Particle Swarm Optimisation (PSO) can be attributed to its simplicity, efficient iterations, and ease of implementation[8]-[9]. Nevertheless, conventional PSO frequently experiences premature convergence and inadequate accuracy in identifying geometric error parameters, resulting in suboptimal outcomes. The population dynamics mechanism of PSO and the pheromone-based learning mechanism of Ant Colony Optimisation (ACO) are integrated in this study to resolve these challenges. The hybrid algorithm that has been proposed improves the local search capability of PSO and utilises the global exploration efficacy of ACO to prevent the optimisation process from becoming ensnared in local optima.[10] to[12].

The BWPSO-RP algorithm, which is a novel hybridization-based stochastic perturbation PSO algorithm with a linearly decreasing inertia weight, is also introduced by the proposed approach. This method enhances population diversity and prevents early convergence by drawing inspiration from the stochastic behaviour of hybrid PSO and artificial fish swarm algorithms[13]-[15]. The global search capability is further improved by the linearly decreasing inertia weight, which guarantees improved convergence accuracy in complex error models[16]. Ant Colony Optimisation (ACO) is a bio-inspired optimisation algorithm that employs pheromone-based information sharing to efficiently investigate global solutions in combinatorial optimisation problems[17]. Although PSO is extremely effective in continuous optimisation tasks, its efficacy is improved by the integration of ACO's pheromone-guided search, which enhances both exploration (global search) and exploitation (local search) processes[18]. This combination prevents PSO from becoming ensnared in suboptimal solutions, resulting in improved error parameter identification. Zhang et al. (2018) demonstrated that the accuracy of parameter identification in autonomous systems is improved by ACO-PSO hybrids, as ACO accelerates convergence and increases population diversity[19]. Furthermore, the detection of global optima in intricate robotic error models, such as the D-H framework, is enhanced by adaptive weight adjustments in PSO, which are guided by pheromone trails in ACO[20].

Recent research has underscored the efficacy of hybrid ACO-PSO algorithms in overcoming the constraints of conventional optimisation techniques. ACO-PSO hybrids have been effectively implemented by researchers in six-degree-of-freedom (6-DOF) robots. In this approach, ACO initialises global parameters, while PSO iteratively refines geometric parameters, resulting in substantial reductions in positioning and orientation errors[21]. In addition, Wang et al. (2021) demonstrated that the D-H model's convergence is expedited, and parameter identification accuracy is improved by pheromone-guided emphasis on critical geometric parameters[22]. These studies verify that hybrid ACO-PSO algorithms enhance convergence speed, enhance global search efficiency, and fortify local search capabilities, rendering them a reliable option for robotic error compensation. The objective of this investigation is to verify the efficacy of the proposed ACO-PSO hybrid algorithm through simulation experiments. The algorithm's capacity to improve geometric parameter identification and localisation error compensation is exhaustively examined through the application of the D-H error model. The findings of this investigation will offer valuable insights into hybrid optimization methodologies for robotic calibration and create new opportunities for high-precision industrial applications.

There are 5 sections in all in this manuscript. Section 1 shares the background related to current techniques implementing Precise Localization and Geometric Error Reduction in Industrial Robots. Section 2 shares the dynamic model of KR10R1420 robot (KUKA Deutschland GmbH, Augsburg, Germany) and D-H representation. One may find the details of our proposed algorithm and methodology in section 3 whereas section 4 discusses the simulation results along with an exhaustive explanation. Last but not least is the conclusion section of the manuscript, which is described in Sect. 5 together with some future recommendations and directions.

2 D-H Model of KR10R1420 Robot

This work utilized a KUKA KR10R1420 robot, a six-degree-of-freedom tandem industrial robot featuring six rotary joints, as seen in Fig. 1[17]. The DH model employed in industrial robotics, together with the coordinate system of the proposed robot, is formulated using the DH approach, as seen in Figure 2 below[17]:

Figure 1 illustrates the KR10R1420 robotic arm, emphasizing its six rotational joints (A1 to A6). Every joint provides one degree of freedom (DOF), allowing the robot to execute intricate spatial maneuvers. The numbered axes (A1-A6) denote the principal rotating axes of the robot, essential for delineating the robot's kinematic chain and comprehending the propagation of positional and orientation faults throughout its structure. This visual depiction corroborates the D-H parameterization employed in the error model.

The illustration in Figure 2, depicts the coordinate

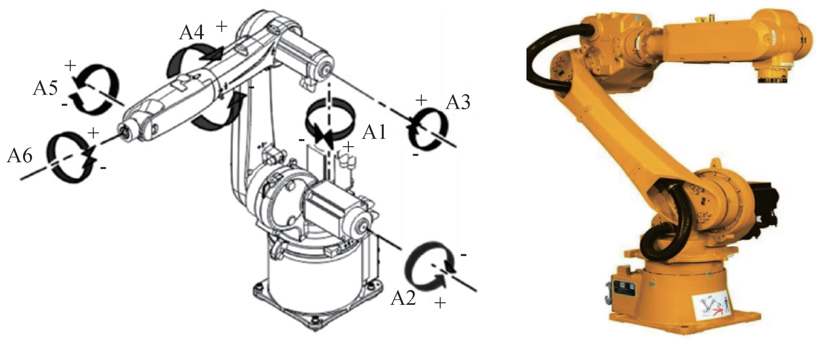

Fig.1 KR10R1420 Robot with six-degree-of-freedom

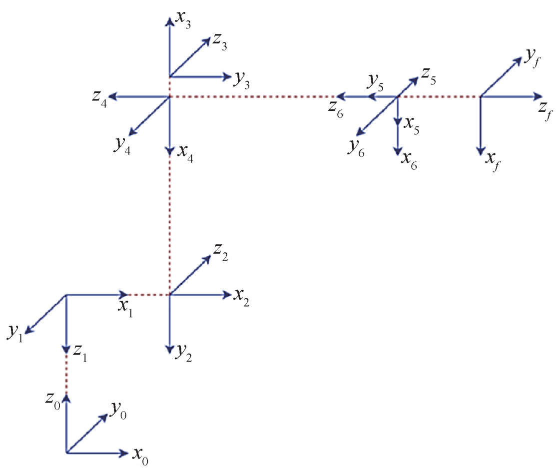

Fig.2 KR10R1420 Robot with Coordinate System

Table 1 Nominal geometric parameters of KUKA robot

$joint_i$	a_i/mm	α_i /deg	d_i/mm	θ_i/deg
1	150	−90	450	−185-185
2	610	0	0	−155-35
3	20	−90	0	−130-154
4	0	90	660	−350-350
5	0	-90	0	−130-130
6	0	0	160	−350-350

Table 2 Geometric parameters errors of KUKA robot

$joint_i$	Δa_i/mm	$\Delta\alpha_i$/rad	$\Delta\theta_i$/rad	Δd_i/mm
1	−0.16	−0.01	−0.02	0.18
2	−0.04	0	0.01	−0.13
3	−0.01	0.03	0.0	0.21
4	0.11	−0.01	−0.03	−0.06
5	0.22	0.0	0.01	0.05
6	0.05	−0.02	−0.02	0.08

system corresponding to each joint of the KR10R1420 robot, in accordance with the Denavit-Hartenberg (D-H) convention. The axes X_i, Y_i and $Z_i\,(for\ i=1\ to\ 6)$ represent the local reference frames for each link and joint. These frames delineate the geometric parameters, including link lengths, offsets, and joint angles, which are crucial for kinematic modeling and error detection. The transformation matrices obtained from these parameters constitute the foundation of the robot's geometric error model. In the context of our proposed research, these drawings illustrate the fundamental geometric and kinematic configuration that the enhanced particle swarm algorithm (incorporating ACO principles) would refine. Identifying and rectifying geometric error parameters can substantially improve the robot's positioning accuracy, as demonstrated by the simulation trials presented in the research. The proposed algorithm's validity was confirmed using the KR10R1420 robot produced by Kuka Robotics Ltd. The parameters of the DH model for the KR10R1420 robot are presented in Table 1. The inaccuracies of the geometric parameters are presented in Table 2[17].

The error is randomly generated within the intervals of [-0.25, 0.25] mm and [-0.05, 0.05] rad. This error value is incorporated into the nominal geometrical parameters of the robot presented in Table 1 to derive the actual joint angle. Subsequently, the difference between the actual and theoretical joint angles is calculated to determine the adaptation value. Moreover, the fitness function used is shown in equation (1) below:

$$F=\min\left(\sum_{i=1}^{N}\sqrt{((\delta P_{xi})^2+(\delta P_{yi})^2+(\delta P_{zi})^2})\right) \tag{1}$$

In the above equation (1), the term $'N'$ denotes the number of robot error sampling points, and in this paper, it is proposed as 20. F is function of $(\Delta a_i, \Delta d_i, \Delta a_i, \Delta\theta_i,)$, which represents the error ensemble of N points, When the robot traverses space, the disparity between the nominal position of each point and its real position is determined by sampling various points. The enhanced particle swarm algorithm is employed to ascertain the precise values of the error parameters, hence facilitating error compensation for the robot and enhancing the end positioning accuracy of the industrial robot. The fitness function in Equation (1) minimizes the cumulative positioning error by evaluating deviations in the x, y, and z coordinates, ensuring precise geometric parameter identification for industrial robots. Our hybrid optimization algorithm integrates Particle Swarm

Optimization (PSO) with Ant Colony Optimization (ACO) to overcome PSO's limitations such as local optima trapping and accuracy issues. By incorporating pheromone-based learning from ACO, the approach enhances global search efficiency and convergence accuracy. Additionally, the Denavit-Hartenberg (D-H) method is utilized to refine error modeling, further improving kinematic precision. This integration results in a more robust and high-precision optimization framework, making it highly suitable for industrial robots requiring superior accuracy and efficiency

3 Proposed Algorithm

The conventional particle swarm optimization (PSO) approach is frequently employed to ascertain the geometric error parameters of industrial robots. Nonetheless, owing to its stochastic characteristics and the finite particle count within the swarm, Particle Swarm Optimisation frequently experiences premature convergence when addressing high-dimensional, constraint-based optimization challenges. The optimization of geometric error parameters entails a high-dimensional search space, rendering the solution susceptible to convergence at local optima. To address these constraints, we present an augmented PSO algorithm that incorporates the principles of ant colony optimization (ACO), therefore enhancing both exploration and exploitation capabilities. The pheromone mechanism of ACO effectively directs agents towards optimal routes through collaborative reinforcement, facilitating thorough exploration of the search space. In our proposed integration, the global best particle (P_g) in PSO employs ACO-inspired pheromone trails to investigate new areas of the search space throughout each iteration. The pheromone value specifically affects the movement probability of the global best particle, enabling it to consider the historically ideal paths recognized by other particles. The procedure for updating P_g is as follows:

$$P_g^{new} = P_g + \alpha.pheromone(t).\Delta X \tag{2}$$

where α is a scaling factor, and *pheromone*(t) denotes the pheromone intensity at time t, while ΔX signifies the directional step size obtained from local particle interactions. This ACO-based approach enhances global search capacity by diminishing the probability of convergence at local optima. Furthermore, to mitigate the decline in diversity during the later phases of PSO convergence, ACO-inspired probabilistic path exploration is included at the population level. In each iteration, a selection of particles is randomly modified according to a probabilistic pheromone effect. The particle's new location is ascertained by:

$$X_{new} = X.(1 + rand.pheromone(t)) \tag{3}$$

Where *rand* is a random number within the interval between 0 and 1. The fitness of perturbed particles is compared with the global best particle, and higher fitness particles are used for updating pheromone trails. This stochastic perturbation ensures the population maintains diversity, thereby enhancing the exploration capability of the algorithm and preventing the solution from reaching premature convergence. We propose PSO by hybridizing ACO principles with an adaptive weight adjustment technique. In Particle Swarm Optimisation (PSO), inertia weight (w) is gradually decreased over iterations in order to balance the exploration and exploitation.

$$w = w_{max} - \frac{T}{T_{max}} \cdot (w_{max} - w_{min}) \tag{4}$$

In the above equation, T is the current iteration, while T_{max} represents the maximum iteration. T_{max} is the total number of iterations, w max is the beginning weight, and w_{min} is the ultimate weight. This ensures a smooth variation of particle velocity from a global search focus to a local search focus with the advancement of the algorithm.

The procedure of the proposed combined PSO-ACO algorithm begins with the initialization of the particle swarm, the ACO pheromone values, and the computation of the fitness values for all particles. Subsequently, the particle swarm is updated by modifying the velocity and position of the particles through the conventional PSO formula, including an adaptive weight adjustment mechanism that equilibrates exploration with exploitation. In global optimization, the position of the global best particle is enriched by ACO's pheromone-guided behavior, and if its updated position improves the fitness value, it replaces the new global best. In order to maintain the diversity in the population, a set of particles is randomly perturbed using ACO-inspired stochastic behavior, and their fitness values are computed followed by updating the pheromone trails based on the best-performing particles. The procedure iteratively persists, reiterating the particle swarm update, global optimization, and population-level diversification phases until a termination criterion is satisfied. Upon conclusion, the algorithm produces the global optimal solution along with the specified geometric error parameters of the industrial robot. The amalgamation of ACO's pheromone-driven exploration with PSO's population-centric dynamics markedly enhances the algorithm's capacity to optimize geometric error parameters efficiently.

4 Simulation Results

The robot's geometric parameters are determined via the enhanced PSO algorithm through the integration of ACO in MATLAB software. Regarding the enhanced particle swarm selection: The population count is 200, with learning factors c_1 and c_2 both set to 1.49. The inertia weights are w_{max}=0.8 and w_{min}=0.4. The coefficient of variation for the populations during the algorithm's iterative process is p_m=0.2. The coefficient for the iterative process of the globally optimal solution is

$P = i$, where i represents the current iteration number of the particle swarm, along with the direction. T is established at 200, representing the total number of iterations for the particle swarm. The step size is established at 2. The iteration limit is established at 200. Our proposed algorithm has been compared with another algorithm as well and is averaged across 6 iterations and the average fitness values for each algorithm are presented in Table 3 below:

Table 3 Comparison of experimental results

Arithmetic	PSO	WPSO	BPSO	PSO + ACO
Average adaptation	5.39	4.02	4.58	3.12

The Average Adaptation metric in Table 3 represents the mean fitness value across multiple iterations for each algorithm, assessing its convergence behavior and optimization efficiency. It is calculated as:

$$F_{avg} = \frac{1}{N}\sum_{i=1}^{N} F_i \tag{5}$$

where F_i is the fitness value at the i-th iteration and N is the total number of iterations. A lower average adaptation value indicates a more effective algorithm in minimizing positioning errors and enhancing optimization precision. As seen in Table 3, WPSO is the weighted particle swarm algorithm, BPSO is the hybridization-based particle swarm algorithm (BPSO) and PSO + ACO is our proposed algorithm. Table 3 indicates that the conventional PSO algorithm achieves an average fitness of 5.39 across 6 iterations, representing the least effective iteration outcome. Secondly, the average fitness value of six iterations of the BPSO algorithm is 4.58, while the WPSO demonstrates a performance of 4.02. In contrast, the PSO with an integration of ACO algorithm proposed in this paper exhibits superior iteration efficacy, achieving an average fitness value of 3.12, representing a substantial enhancement in iteration precision relative to several other conventional particle swarm algorithms.

The iterative trend of the enhanced particle swarm technique is illustrated in Fig. 3. Table 3 illustrates that the enhanced particle swarm algorithm, integrated with ACO, exhibits superior convergence accuracy in updating speed and position information compared to the conventional particle swarm algorithm, as it optimizes both the optimal particles and the population's iterative

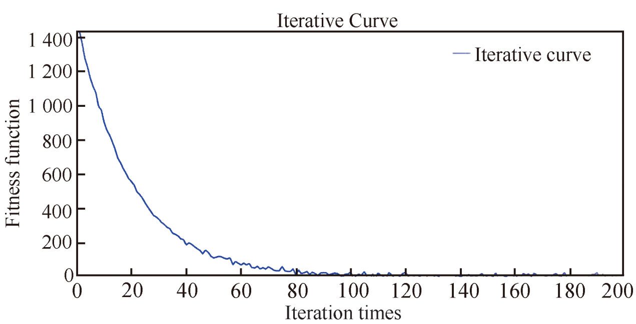

Fig.3 Iterative curve of algorithm

process. The comparison of the X, Y, Z axis errors and absolute position error of the robot prior to and subsequent to the optimization of the enhanced particle swarm algorithm is as follows:

Figure 4 and 5 illustrate that prior to error compensation, the X, Y, Z axis errors of the industrial robot fluctuate between [-100, 150] mm, with a maximum error of approximately 150 mm. Conversely, following error compensation, the X, Y, Z axis errors oscillate between [-1.25, 0.75] mm, with a maximum error of around 0.75 mm. This indicates that the error along the X, Y, Z axes of the robot is substantially reduced after compensation using the enhanced PSO algorithm integrated with ACO.

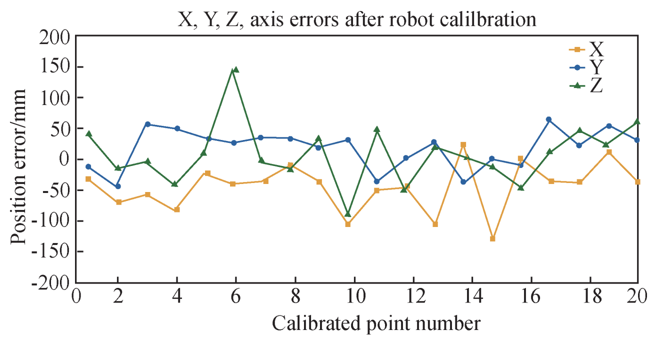

Fig.4 X, Y and Z axis errors before calibrating robot

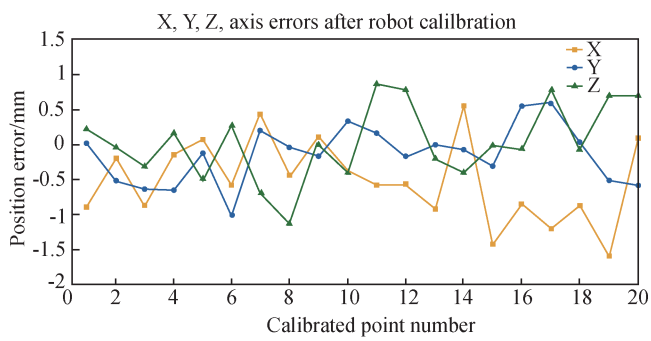

Fig.5 X, Y and Z axis errors after calibrating the robot

Figures 6 and 7 illustrate that the absolute position error of the robot fluctuates between 10 mm and 45 mm prior to error compensation, with a maximum error near 45 mm and a minimum near 10 mm. post-compensation, the absolute position error oscillates between 0.05 mm

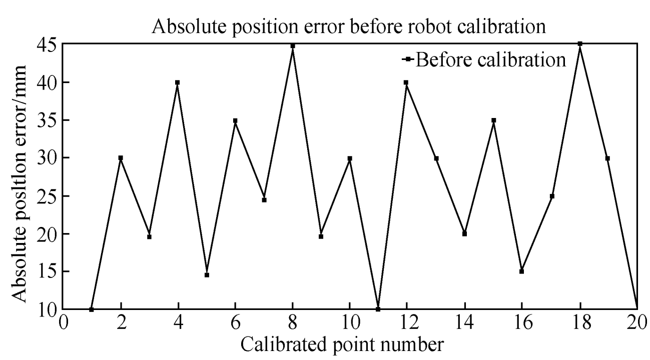

Fig.6 Absolute position error before robot calibration

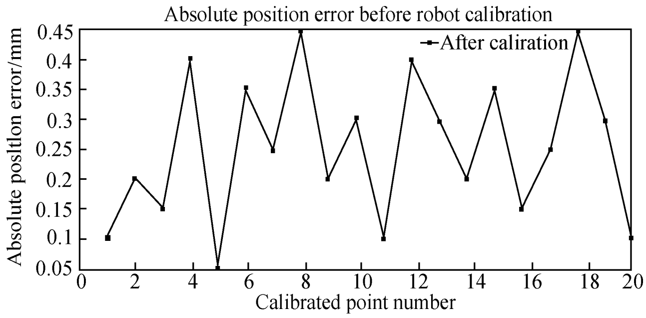

Fig.7 Absolute position error after robot calibration

and 0.45 mm, with the minimum error approaching 0 mm and the maximum error around 0.45 mm. Consequently, the enhanced PSO algorithm significantly enhances the positioning accuracy of industrial robots. When considered alongside Table 3, it is evident that the stability of the PSO integrated with ACO algorithm is likewise ideal. One might require knowing the values for c_1 and c_2 , these values are based on empirical validation and optimization theory, the cognitive (c_1) and social (c_2) learning factors were established at 1.49 during the simulation verification procedure. This choice guarantees an optimal equilibrium between exploration (global search) and exploitation (local search), thereby enhancing the accuracy of the solution and averting premature convergence. In PSO-based optimization problems, particularly in robot calibration tasks, the values of c_1 and c_2 within the range [1.4 - 1.6] are widely acknowledged. The proposed PSO-ACO hybrid optimization approach is enhanced in precision and stability by the setting of $c_1 = c_2 = 1.49$, which maintains robustness and enhances the algorithm's ability to converge effectively.

5 Conclusion

This paper introduced an improved Particle Swarm Optimisation (PSO) method combined with Ant Colony Optimisation (ACO) for the calibration and error compensation of industrial robots. The improved method has shown notable advancements in convergence accuracy, optimization precision, and overall placement accuracy relative to conventional PSO and its derivatives, including Weighted PSO (WPSO) and hybrid PSO (BPSO). The method was evaluated using a population size of 200, with learning factors c_1 and c_2 established at 1.49, and inertia weights varying from $w_{max} = 0.8$ to $w_{min} = 0.4$. The mutation coefficient (p_m) was 0.2, and the iterative process coefficient for the globally optimal solution was directly proportional to the current iteration number ($P=i$). The total number of iterations (T) was 200, with a step size of 2. The algorithm's efficacy was assessed throughout six iterations, with the suggested PSO+ACO attaining an average fitness value of 3.12, representing a notable enhancement relative to PSO (5.39), WPSO (4.02), and BPSO (4.58). Figures 4 and 5 demonstrate that the errors along the X, Y, and Z axes prior to optimization varied between −100 mm and 150 mm, with a maximum error of 150 mm. Following optimization, these errors were diminished to the interval [− 1.25, 0.75] $[-1.25, 0.75]$ mm, with a peak error of 0.75 mm, signifying significant error compensation. Figures 6 and 7 illustrate that the absolute position inaccuracy of the robot diminished from a range of 10 mm to 45 mm prior to compensation to 0.05 mm to 0.45 mm subsequent to correction. The maximum absolute position error was reduced from 45 mm to 0.45 mm, reflecting a significant enhancement in the precision of positioning. Iterative trends, as shown in Figure 3, indicate that the improved PSO method and ACO optimize not only the placement of particles but also the iterative process of the population more effectively compared to traditional algorithms. ACO improves both the global and local functions of the search, hence enhancing the convergence speed and accuracy. It outperformed the common PSO variants in the three aspects of precision, stability, and convergence velocity. The decrease in the position error in the X, Y, and Z axes and the absolute position error shows its effectiveness in industrial robotic calibration tasks. These results have established premises for further research on the hybrid optimization methodology on robotic error compensation and other high-precision applications.

Future Recommendations and Directions

Several avenues for future research are recommended in light of the promising results of this study. Tests of the upgraded PSO + ACO will be tried with a wider class of industrial manipulators with different kinematics structures to confirm its general results. Furthermore, embedding automatic methods for adaptively determining the parameters will certainly play a fundamental role in allowing the algorithm to improve in operating contexts that can be varied. Improvements could include real-time optimization capabilities that would make immediate calibration possible during robotic operation. Hybridization with other metaheuristic algorithms, like GA or DE, may be carried out in the search for improved convergence velocity and precision. Finally, this methodology could be applied to multi-robot or swarm robot systems, which could offer new perspectives on the enhancement of collaborative activities in industrial automation. These potential directions would serve to improve the algorithm, increasing its applicability to complex robotic systems. The primary objective of this study is to compare the proposed hybrid PSO-ACO algorithm with PSO and its derivative approaches. However, future research will expand the analysis by incorporating additional parameter optimization techniques, including Genetic Algorithms (GA), Simulated Annealing (SA), and Grey Wolf Optimiser (GWO). The proposed method's robustness and efficacy in optimizing robotic system parameters for industrial applications will be more comprehensively evaluated through this broader benchmarking.

Author Contribution:

Ghulam E. Mustafa Abro and Eman Mahmoud conceptualised and developed this research. Abro oversaw simulations, computational modelling, and software development, while Eman curated, analysed, and visualised data. Eman managed resources and Abro oversaw project administration to validate outcomes. Eman edited and Dr. Abro reviewed the edited manuscript. Both writers evaluate and approve the final manuscript.

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The authors declare no competing interests.

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