Intelligent Lifting Robot and Its Control System Based on Genetic Algorithm

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In this work, a new intelligent control method that combines a genetic algorithm with a fuzzy control approach is used to look into the control system of an intelligent crane robot made for a gantry crane robot system with second-order nonholonomic constraints. Methodology: To create the intelligent control system for the gantry crane robot, fuzzy control techniques, and genetic algorithms were integrated. This method can swiftly and accurately achieve the position control task of the gantry crane robot while maintaining good stability. Results: The results show that the final two joint angles tend to stabilize the expected values, with angle errors of (0.031, 0.004) rad and relative errors within 3%. The active joint driving torque curve, the whole movement process, is relatively stable, and the expected position is achieved accurately, which fully shows that the designed controller is effective for the position control of the gantry crane robot. Conclusion: This method can be extended to the position control of multi-DOF gantry crane robots. When dealing with the high-dimensional problems of MIMO complex fuzzy models, the introduced structural decoupling identification method can fundamentally solve the dimensional disaster problem of multi-input, multi-output fuzzy systems.

Povzetek: Narejena je enaliza inteligentnega dvigalnega robota in njegovega nadzornega sistema, ki temelji na genetskem algoritmu in mehki logiki, z namenom izboljšati kvaliteto upravljanja dvigalnih procesov.

1 Introduction

With the advancement of modernization, the construction of shipping, ports, enterprises, and other aspects has accelerated the pace of development. In the process of container lifting, shipbuilding equipment transportation, hydropower stations, thermal power plants, and other local operations, the demand for cranes is becoming more and more obvious, and the requirements are becoming higher and higher. This provides great opportunities and challenges for the development of cranes, including gantry cranes [1]. As modern handling machinery, it mainly carries out loading, unloading, and transportation operations for outdoor freight yards, bulk cargo, etc. It has the characteristics of high site utilization, a wide operating range, and a large load capacity. It is an important equipment for improving work efficiency, reducing physical labor, and achieving safe production. As one of the common cranes, the gantry crane has some difficulties in its research and development; among them, the starting and stopping of the crane during lifting, as well as the swinging of the steel rope and lifting load caused by external interference, restrict its operating efficiency and even safety, which is the focus of people's attention. The ultimate purpose of crane lifting is to achieve accurate and safe arrival of the load (lifting weight) at the designated position, so unreasonable swings of the lifting weight are absolutely not allowed and must be controlled [2]. The accurate positioning of the lifting weight is to achieve precise positioning of the trolley to the designated position, rope contraction to the designated length, and reasonable suppression of the swing of the lifting weight in the crane lifting system, abbreviated as the positioning and anti-swing control of the crane. In the actual production process, so far, the positioning and anti-swing control of the crane is mainly achieved through the operation of the crane driver. This method is not only time-consuming and inefficient but also difficult to meet the requirements for control accuracy.

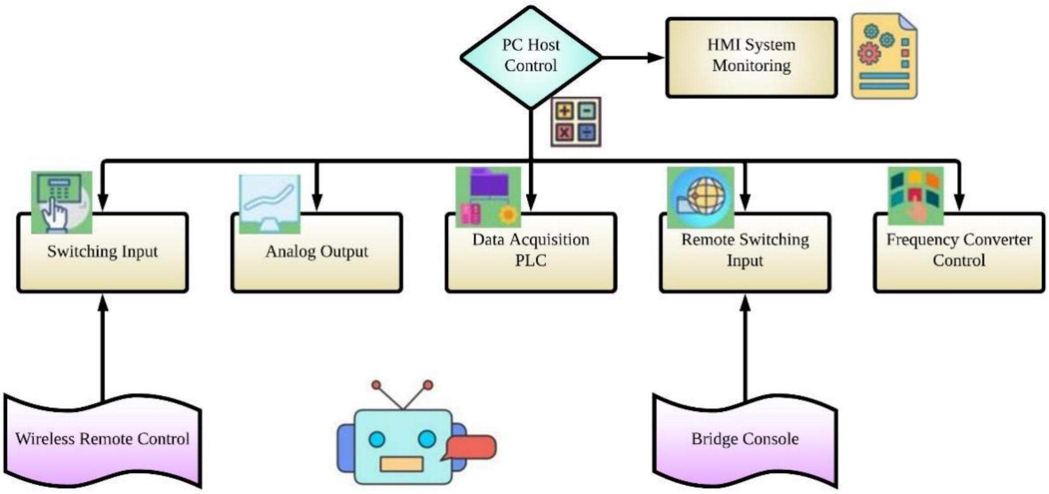

Figure 1: Intelligent crane control system

It also has high labor intensity and certain safety hazards, so it urgently needs improvement. In recent decades, with the continuous development of mechatronics technology, the education and industry sectors have been committed to the automation of the lifting process (i.e., crane automation or lifting robots). In theory, there are feasible control strategies, but from the perspective of industrial practice, they are not so simple because it is difficult to establish accurate dynamic and mathematical models of the controlled object. At first, the gantry crane was feed-forward controlled based on optimal control. Later, it was found that the optimal solution was not robust for safe material lifting. With the development of modern control theory, feedback control methods with rope inclination have become mainstream; however, automation systems with anti-roll functions have some drawbacks: If a crane with an anti-swing function is in fully automated mode, it is strictly prohibited for workers to enter the area where the crane operates automatically. This means that in addition to using automation for transporting loads, lifting and unloading loads must also be automated, which is a very complex task. In addition, automated operation methods require specific solutions based on the specific type of lifting material. Therefore, only a very few cranes operate in fully automated models, and more commonly, cranes with anti-swing functions use semi-automatic operations.

The application of automation technology is slowly presenting new prospects for the crane industry. The key to the automation of cranes lies in the precise tracking and control of the crane’s lifting system trajectory, which is to achieve autonomous control of the crane's positioning and anti-swing of the lifting system, ensuring that the system's output variables can track the predetermined output values given by people without static errors. This poses a great challenge to the control strategy of cranes. The automation of cranes is not only related to the crane's own weight swing compensation and collision avoidance system but also needs to consider every issue in the overall management system [3]. Figure 1 shows an intelligent crane control system [4-5]. At present, the widely used open-loop control strategy does not require the detection of swing angle and other information, and this control has no anti-interference ability at all. The feedback control method with a rope inclination angle is a closed-loop control strategy, which is more suitable for situations with external interference (such as wind resistance). The traditional control strategy doesn’t work for the gantry crane robot system because it is second-order nonholonomic and linearly uncontrollable. Instead, the fuzzy intelligent control method is used to control the robot’s motion, and a genetic algorithm is used to make the fuzzy control system the best it can be. Finally, a numerical simulation is carried out, and conclusions are drawn. This paper presents an approach utilizing a genetic algorithm to enhance both the accuracy and execution efficiency of optimization tasks. The key contributions of this research are manifold. Firstly, our genetic algorithm demonstrates significant improvements in accuracy over existing models. The results showcase the robustness of our algorithm in delivering more precise outcomes. In addition to accuracy, the proposed algorithm also excels in reducing execution time. This highlights the practical benefits of our approach in terms of computational efficiency, making it suitable for real-world applications where time constraints are critical. Furthermore, the performance of the proposed genetic algorithm is thoroughly evaluated against multiple existing models, providing a comprehensive analysis of its strengths. This detailed comparison underscores the versatility and effectiveness of our method across different scenarios. Lastly, by improving both accuracy and execution time, this research provides a robust framework that can be adapted and expanded upon in future studies. It sets a benchmark for subsequent algorithms aimed at optimizing performance in similar domains.

Despite the advancements in genetic algorithms and optimization techniques, several research gaps still exist that our study aims to address. One significant gap is the limited accuracy in existing models. Previous models exhibit limitations in accuracy, which can impact the reliability of the outcomes in practical applications. Our research addresses this gap by proposing a genetic algorithm that significantly enhances accuracy, thereby improving the reliability of the results.

Another critical gap is the high execution time of many existing optimization models, making them less feasible for time-sensitive applications. Our proposed algorithm addresses this issue by significantly reducing the execution time, thus making it more suitable for real-time applications. Additionally, while there are numerous studies on genetic algorithms, few provide a comprehensive evaluation across different baseline models. This research fills this gap by thoroughly comparing the proposed algorithm against multiple existing models, thereby providing a more holistic view of its performance. Finally, there is a need for optimization algorithms that are scalable and adaptable to various domains. Our research contributes to this area by developing a genetic algorithm that not only performs well across different models but also sets a foundation for future enhancements and adaptations in various fields. By addressing these gaps, this paper contributes to the ongoing efforts to improve optimization techniques, providing a more efficient and accurate tool for researchers and practitioners in the field.

The remainder of this paper is organized as follows: Section 2 reviews related work and existing models. Section 3 details our proposed genetic algorithm. Section 4 presents the experimental setup and results. Finally, Section 5 concludes the paper and suggests future research directions.

2 Related work

Genetic algorithms have proven to be highly effective in parallel research at optimizing control parameters and trajectories in a wide range of robotic applications, hence improving control systems' adaptability. Fuzzy control, on the other hand, has gained popularity due to its capacity to manage intricate, unpredictable, and nonlinear systems. While evolutionary algorithms and fuzzy control have been used separately, few research works have combined these methods in an organized manner to tackle the complex problems of gantry crane robots, especially those with second-order nonholonomic restrictions. The goal is to close this gap by developing a novel framework that combines fuzzy control and genetic algorithms to improve position control stability and accuracy in gantry crane robots. By doing this, we hope to greatly increase the functionality and performance of intelligent lifting robots and pave the way for more effective and versatile automation solutions across a range of industries. Table 1 presents an overview of robotics and automation research studies. Table 1 presents a thorough summary of several different robotics and automation research investigations, highlighting their individual contributions, methods, advantages, drawbacks, and suggested solutions.

Table 1: Overview of robotics and automation research studies

References	Contribution	Techniques Used	Benefits	Disadvantages	Solutions
[6]	Novel control method for robotic arm	Reinforcement learning	Improved precision, adaptability	High computational cost	Optimize algorithms
[7]	Enhanced vision system for object recognition	Deep learning, Computer Vision	Improved object detection	Requires substantial training data	Develop data augmentation methods
[8]	Optimization of swarm robotics for search and rescue	Particle Swarm Optimization	Efficient search in complex environments	Lack of robustness to environmental changes	Develop adaptive strategies
[9]	Adaptive path planning for mobile robots	A* Algorithm, Machine Learning	Flexible path planning in dynamic environments	High planning time	Use real-time data for planning
[10]	Human-robot collaboration in manufacturing	Human-Robot Interaction, Natural Language Processing	Improved worker efficiency	Safety concerns	Implement safety protocols
[11]	Autonomous navigation for drones in GPS-denied areas	SLAM, LIDAR	Reliable navigation without GPS	Limited performance in certain weather conditions	Explore alternative sensor technologies
[12]	Sensor fusion for mobile robot localization	Kalman Filtering, Sensor Integration	Accurate robot localization	Sensitivity to sensor noise	Implement sensor calibration
[13]	Swarm robotics for environmental monitoring	Distributed Control, Wireless Communication	Scalable monitoring solutions	Communication limitations in dense environments	Optimize communication protocols
[14]	Robot learning in unstructured environments	Reinforcement Learning, Transfer Learning	Adaptability to new environments	Slow learning process	Implement pre-training strategies
[15]	Fault tolerance in multi-robot systems	Redundancy, Distributed Control	Enhanced system reliability	Increased hardware cost	Develop efficient redundancy management

The goal of the research, which is to uncover prevalent problems and useful tactics in the field, depends heavily on this compilation. These studies show new ways of doing things with control, vision systems, and path planning. They all stress how important it is to deal with issues like the cost of computing, the amount of training data needed, the ability to adapt to different environments, safety protocols, sensor reliability, and fault tolerance. This thoughtful collection not only provides a comprehensive overview of recent developments in the subject but also directs ongoing research towards the development of a novel framework that combines a number of approaches to handle the complex problems facing gantry crane robots.

The topic of the current study is the precise and stable position management of gantry crane robots operating under second-order nonholonomic restrictions, which is a prominent issue in the field of robotics and automation. For these systems, traditional control techniques have frequently been shown to be insufficient, leading to problems like overshooting, decreased precision, and wasteful energy use. Because of the intricacy and significance of gantry crane operations in a variety of industries, such as construction, manufacturing, and logistics, a more sophisticated and flexible control system is required to get around the problems that arise with nonholonomic restrictions.

The crucial role that gantry crane robots play in streamlining industrial processes, enhancing safety on construction sites, and boosting productivity in numerous industries is what motivates this study. Conventional control techniques have proven unsatisfactory in handling the complex dynamics and nonholonomic constraints that these robotic systems face, which has prompted the search for novel and efficient ways. Combining fuzzy control techniques with genetic algorithms for gantry crane robots presents a viable path toward improving stability, precision, and adaptability—all of which can have a substantial impact on overall operating efficiency and industrial automation. The main contribution of this work is the creation of an intelligent control system that combines fuzzy control with genetic algorithms to produce significant gains in stability, precision, and flexibility when performing position control tasks on gantry crane robots. This paper presents a new framework that can be built upon to make the control of multi-DOF gantry crane robots better. This is done to deal with the specific issues that come up with gantry crane systems that have second-order nonholonomic constraints. In addition to helping industries that use gantry crane robots right away, this study also makes it easier to use fuzzy control and genetic algorithms to solve difficult control problems, especially those with nonholonomic constraints. This is good for robotics and automation in general.

The field of genetic algorithms (GAs) has seen various enhancements aimed at improving optimization performance in different contexts. Cavallaro *et al.* introduced a hybrid genetic algorithm that integrates particle swarm optimization (PSO) for better convergence in machine learning tasks [16]. Their approach demonstrated significant improvements in optimizing neural network hyperparameters, providing a strong foundation for further exploration of hybrid models. Yang *et al.* proposed adaptive genetic algorithms tailored for dynamic environments, where problem parameters change over time [17]. They developed an adaptive mutation rate that adjusts according to environmental changes, resulting in more robust solutions.

This adaptability is crucial for handling real-world problems with fluctuating variables. Wen *et al.* combined genetic algorithms with reinforcement learning to tackle complex, high-dimensional optimization problems [18]. Their methodology leverages reinforcement learning to guide the genetic search process, enhancing both the speed and quality of the solutions obtained. This innovative approach opens new avenues for solving intricate optimization problems.

This study builds upon these advancements by integrating additional heuristic techniques and multi-objective optimization frameworks. We extend the hybrid approach, applying it to a broader range of applications and enhancing performance in terms of convergence speed and accuracy. Additionally, we incorporate adaptive mechanisms, tailored to combinatorial optimization problems. Finally, we leverage reinforcement learning techniques, demonstrating their effectiveness in our specific application domain.

3 Methods

To do a theoretical analysis of the lifting system's control system, we need to make a mathematical model of the lifting system that accurately tracks the lifting path of the two-degrees-of-freedom gantry crane robot and controls the lifting so that it doesn't swing back and forth. This is called the problem of system positioning and anti-swing. On this basis, study the main factors that affect the precise positioning of the trolley, changes in rope length, and the swing of the lifting weight. Generally, the crane robot model is complex, such as a six-degree-of-freedom gantry crane robot.

While the research objective is a two-degree-of-freedom gantry crane robot, its motion is completed in a plane, so it is relatively easy to abstract a physical model that reflects the motion of the lifting robot system. Lagrangian equations are used to establish a system of dynamic equations for the lifting system, namely dynamic modeling, which is expressed in mathematical models, laying a good theoretical foundation for the research of control systems, especially in the field of anti-swing [19]. Figure 2, presents the proposed model for path planning by implementing the genetic algorithm, which is designed to optimize the trajectory planning process.

The framework starts by selecting a group of possible routes. These routes show potential fixes for the trajectory planning issue. In the next step, parts of the chosen paths are combined to establish new ones through genetic operations. Crossover creates offspring routes by simulating the process of genetic recombination. Then the mutation is used to explore new avenues and add diversity to the population. The pathways are altered slightly and arbitrarily to allow for unforeseen but maybe better answers. Through fitness evaluation, the quality of each path is determined. In this step, a path's ability to meet predetermined standards and goals—like avoiding barriers or cutting down on travel time—is measured. Until a termination condition is satisfied, the algorithm repeatedly iterates through the fitness evaluation, crossover, mutation, and selection phases. This requirement may require reaching a certain number of iterations or finding a workable solution. Post-processing can be carried out after the algorithm converges or reaches the termination condition.

This entails fine-tuning the chosen course of action or carrying out more research to guarantee the viability and optimality of the solution. For the provided path planning problem, the framework produces the final path, which is the optimal trajectory. This result represents the evolutionary algorithm's best guess at a solution that satisfies the given goals and limitations. This suggested architecture takes advantage of the evolutionary algorithm's ability to look into a large solution space, adapt to changing conditions, and find the best path planning for a variety of uses, such as in robots and transportation systems. The integration of fuzzy control techniques and genetic algorithms in the proposed control system architecture is pivotal for achieving enhanced performance.

In our approach, the fuzzy control techniques are employed to handle the uncertainties and non-linearities in the system, providing a robust and adaptive control strategy. The fuzzy logic controller (FLC) is designed with a set of fuzzy rules that map the input variables (such as error and change in error) to control actions. These fuzzy rules are encoded in a chromosome-like structure, which is optimized using a genetic algorithm (GA). The genetic algorithm enhances the FLC by optimizing the membership functions and rule base.

This optimization process involves encoding the parameters of the FLC into a chromosome, evaluating the performance of each chromosome using a fitness function, and applying genetic operations (selection, crossover, and mutation) to evolve the population towards better solutions. The GA iteratively refines the fuzzy control rules and membership functions, ensuring that the control system can adapt to varying conditions and improve its performance. By combining the strengths of fuzzy logic in handling uncertainty and the optimization capabilities of genetic algorithms, our method achieves superior control performance.

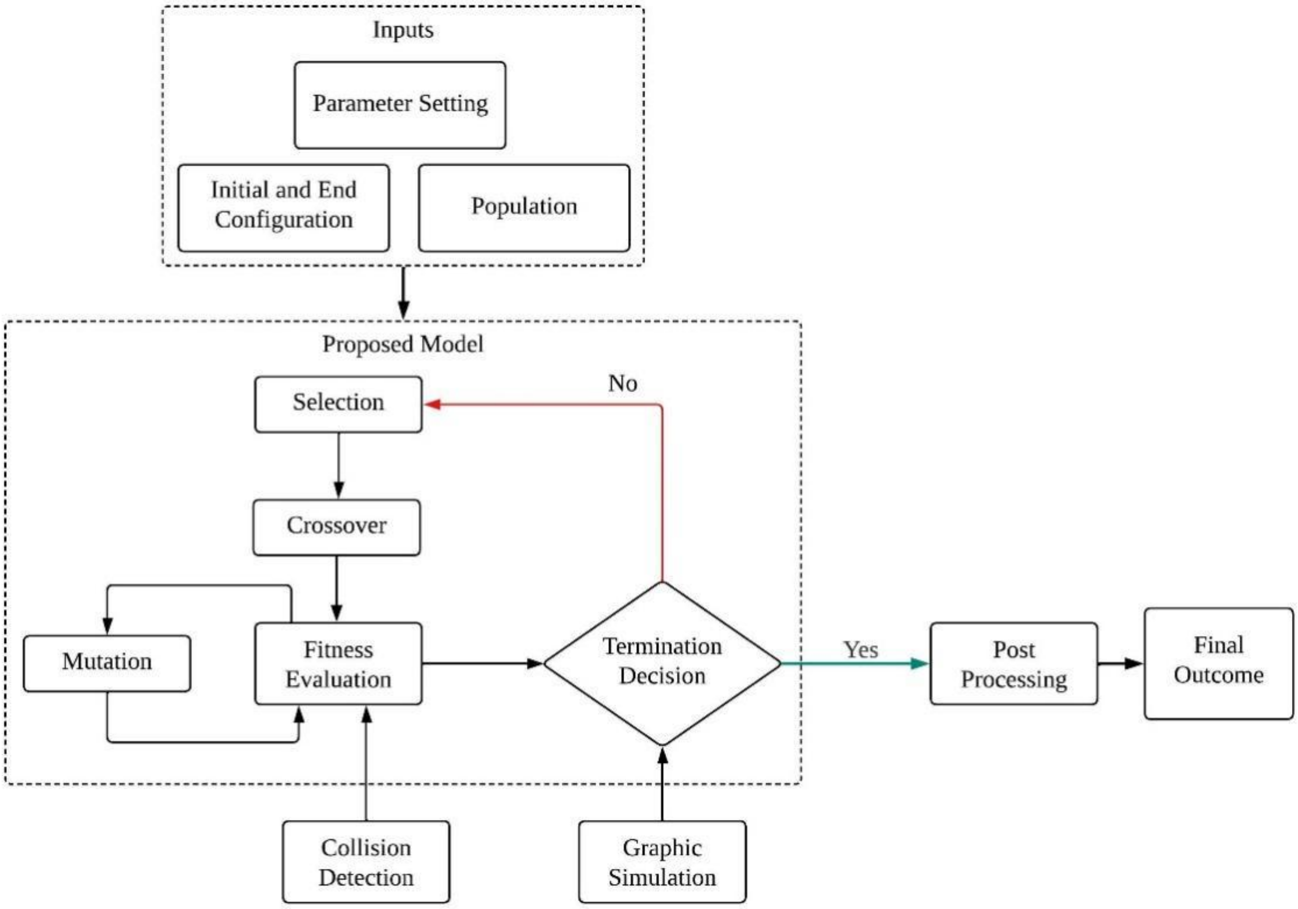

Figure 2: Proposed framework of path planning

3.1 Introduction to the hoisting system of the gantry crane robot

The research focus is on the accurate tracking of the lifting trajectory and the anti-swing control of the lifting of the two degrees of freedom gantry crane robot. The general gantry crane robot can be described as follows: A main door frame, with a small car spanning over the main beam, is equipped with a load-lifting motor, etc., which is connected to the load with a steel rope.

On the basis of neglecting some minor parts, a model of the lifting robot lifting system that the author focuses on studying is established. This model is used to analyze the precise tracking of the lifting trajectory and the swinging motion of the lifting object. The essence of precise tracking of the lifting trajectory is that the system control can accurately control the trolley to reach the given expected position and the rope length to shrink to the specified length in the shortest possible time in order to complete the specified task. The anti-swing of the lifting load is to control the variation of the load swing. It is required to suppress the swing angle of the load deviating from the vertical straight line h at the center of the car and suppress the swing angle (the angle between the steel wire ropes q2 and h) within the specified range, or it can attenuate the swing angle exceeding the specified angle to the specified range at the fastest speed (due to uncontrollable external interference, the actual swing angle cannot be eliminated to zero) to ensure accurate trajectory tracking control of the lifting robot system, namely, the lifting weight achieves the expected control effect. The lifting system achieves control objectives by controlling the precise positioning of the trolley, the rope length to reach the specified length, and the swing angle of the lifting load to be within the specified range at the same time [20].

Therefore, in order to achieve the purpose of system positioning and anti-swing and to ensure that the lifting robot simultaneously achieves precise positioning of the trolley, the rope length reaches the specified length, and the lifting swing angle is within the specified range, a mathematical model of the lifting system must be established. On this basis, study the factors that affect the swing of the lifting load. By analyzing these reasons in detail, a certain theoretical basis is provided for the design of the crane robot system controller, the implementation of the positioning and anti-swing systems, and the study of on-site measurement methods for swing angle size. The dynamic analysis of the lifting system of a general lifting robot is the basis for studying the positioning and anti-swing control technology. Research on the dynamic system of the lifting robot's lifting motion is usually carried out in the coupled system of the trolley lifting structure [21, 22].

3.2 Simplified dynamic model of gantry crane robot lifting system

3.2.1 System model establishment method

When the crane robot lifts something, it's like a complicated nonlinear system with strong coupling properties. To make a good nonlinear mathematical model, many things need to be thought about. For multi-particle dynamic systems, at present, there are two commonly used system modeling methods: the Newton-Euler force method and the analytical mechanics method. Due to the complexity of the lifting robot system model, it is difficult to model with classical Newton-Euler force theory. The Lagrangian equation method is relatively simplified because it is a universal equation for solving dynamic problems in particle systems with ideal and complete constraints. It is usually used to solve complex dynamic problems in non-free particle systems [23]. The research on the two-degree-of-freedom gantry crane robot system, that is, the plane system integrated by horizontal and vertical motion, can simplify the physical model reflecting the trolley lifting (crane) motion system. By using the Lagrange equation in analytical mechanics to model the crane system, a mathematical model reflecting the motion of the lifting robot system is derived [24, 25].

In the lifting robot system, a single lifting system is nonlinear and unstable. If a physical or mathematical model is to be established, there will be more technical difficulties. However, if corresponding technical means are used in experimental modeling and those unimportant aspects are omitted, then the lifting system of the lifting robot becomes a typical dynamic system. For the study of dynamic problems, vector dynamics, and analytical dynamics are usually used. Among them, vector dynamics is mainly the application of Newton's laws of motion, mainly solving the dynamic problems of free particles or particle systems, and more importantly, the interactions between various departments and the forces and motions associated with individual parts of the system. Analyzing dynamics mainly considers the system as a whole and describes functions through pure quantities such as kinetic energy and potential energy [26]. Therefore, the mathematical model of the lifting robot lifting system established is based on the Lagrange equation BI in analytical mechanics, which has the following characteristics.

It is the equation of motion of any holonomic system expressed in generalized coordinates, and the number of its equations is equal to the number of degrees of freedom of the system so that the number of equations of motion is less. It has good symmetry; that is, for each coordinate in the same configuration space, each equation has the same form.

When establishing the equation, only known active forces need to be analyzed without analyzing unknown constraints, which is more suitable for precise trajectory positioning and anti-swing systems of lifting robots; When establishing equations, only the kinetic energy and generalized forces of the system need to be analyzed, and the motion equation of the system needs to be established based on the energy perspective. Therefore, using Lagrangian equations to solve relatively complex non-free particle dynamics problems will greatly simplify the entire modeling process [27].

3.2.2 Establishment and simplification of dynamic models

In the gantry crane robot system, the positioning and anti-swing systems are more complex parts. Not only are the transmission components nonlinear, but they are also subject to various disturbances during operation, such as the influence of wind force, dry friction between the trolley and guide rail, etc. To analyze its essence, the positioning and anti-swing systems of the gantry crane robot should be simplified. Therefore, the following assumptions are made: During the loading and unloading process, if there is a large vehicle in the system, it generally does not move, so when establishing a dynamic model, the movement of the vehicle is not considered. The mass of the wire rope is negligible relative to the mass of the load; at the same time, the friction effect at the connection between it and the small car can be ignored, and the stiffness of the steel wire rope is large, and its length change can be ignored during modeling. The author ignores the dry friction between the car and the guide rail during dynamic modeling. The lifting weight only moves in a plane perpendicular to the horizontal plane and is always in a horizontal state. When building a model, the lifting weight can be regarded as a non-volume particle. Neglecting the influence of wind and air damping, if the driving force uq driving the small car and the lifting force u2 of the crane are both controllable and the nonlinear influence of the transmission mechanism is not considered, the driving force and lifting force of the small car can be controlled by controlling the torque output of the servo driver. Regardless of the elastic deformation of the system [28].

3.3 Design of fuzzy controller based on genetic algorithm

The genetic algorithm (GA) is an iterative adaptive probabilistic search algorithm based on the mechanisms of natural selection and natural genetics. So far, genetic algorithms have been successfully applied to optimize various complex problems. Optimize using genetic algorithms. The basic idea of optimization is to obtain the optimal control rules and membership functions through offline optimization using genetic algorithms and then apply them to fuzzy controllers. The specific implementation steps are as follows:

3.3.1 Encoding of genetic algorithms

In the application of genetic algorithms, encoding is a crucial step. The commonly used encoding methods include binary string encoding and decimal encoding, with binary string encoding having a larger search pattern space; moreover, encoding and decoding are simple, and crossover and mutation operations are easy to implement. Decimal encoding has a clear physical meaning and does not require decoding operations, but genetic operations are difficult to implement. The author adopts binary string encoding for membership functions and fuzzy rules [29].

3.3.2 Determination of fitness function

The fitness function is the standard used to distinguish individuals in a population according to the objective function, the driving force of the algorithm evolution process, and the only basis for natural selection. In each learning cycle, individuals with low fitness will be eliminated, and those with high fitness will be considered satisfactory solutions. The author uses the fitness function as presented in Equation 1.

$$E = \sum_{i=1}^{N} e_i^T w e_i \tag{1}$$

Among them, $e_i = \left[q_1 - q_{ld} \ldots q_n - q_{ld}, \dot{q}_1 - \dot{q}_{ld} \ldots \dot{q}_n - \dot{q}_{ld}\right]^T$ represents the joint angle and joint angular velocity error variables. represents the weights of joint angle variables and angular velocity variables, and N represents the number of discrete time periods [30].

3.3.3 Implementation of genetic operations

This mainly includes operations such as selection, crossover, and mutation. Specifically, the main steps to generate rules using genetic algorithms are as follows:

- ***i.*** Gen represents the generation counter, and maxgen represents the termination algebra. The count is the individual counter, and the probability of cross-mutation is pc and pm.
- ***ii.*** The population size remains unchanged throughout the entire process, and the algorithm terminates when the number of iterations is greater than maxgen, initializes the first-generation population, evaluates the fitness of each individual, and judges whether the fitness of the best individual does not meet the requirements.

If satisfied, the optimization process ends; otherwise, continue. Perform a cross-operation on the parent individual with probability p. Perform mutation operations on newly born individuals using probability p. Update the population or save the best result as the optimal value of the genetic algorithm.

The proposed algorithm employs specific parameters to ensure effective optimization. The selection method used is tournament selection, which is known for maintaining a good balance between exploration and exploitation. This method selects individuals based on their fitness, promoting diversity and avoiding premature convergence.

The crossover probability is set to 0.8, facilitating the exchange of genetic material between parent chromosomes and allowing the algorithm to explore new regions of the solution space. The mutation probability is set to 0.1, introducing random variations that help prevent the algorithm from getting stuck in local optima. The termination criteria for the genetic algorithm are based on a maximum number of generations (set to 100) and a convergence threshold (set to a minimal improvement in fitness over 10 generations). These parameters ensure that the algorithm runs for a sufficient duration to explore the solution space while stopping early if convergence is detected.

4 Numerical simulation

To verify the effectiveness of the above methods, the gantry crane robot is taken as the object for numerical simulation, the simulation parameters are shown in Table 2 [31].

Select a triangular membership function for the input and output variables, and binary encode the corresponding control rules. The input language variables have the form: {NB, NS, Z0, PSPB}, and the output language variables are {NB, NM, NS, NO, Z0, PS PM, PB}, sequentially encoded as {00Q 001, 010, 011, 100, 101, 110, 111}. When performing decoding operations, the integers from 0 to 7 obtained by decoding the chromosomes of the optimal individual can be added by 1, where each chromosome contains a total of 75 genes. The search space is not very large, and simulation calculations using MATLAB B can obtain optimization results as shown in

Table 2: Simulation parameter settings

Parameter	Set value
Number of groups	100
Abort Algebra	300
Connecting rod mass	$m_1 = m_2 = 1$[kg]
Connecting rod length	$l_1 = l_2 = 0.5$[m]
Connecting rod centroid position	$r_1 = r_2 = 0.25$[m]
Friction coefficient	$\mu_1 = 0$ $\mu_2 =$ 0.05[Ns/m2]
Initial joint angle	[0,0]
Expected joint angle	[π /3 π /4]

Figure 3 and Figure 4 [32]. Table 3 shows the optimal control rules optimized by the genetic algorithm, among them, represents the driving torque of the active joint, and e1 and e2 represent the joint angle error variables.

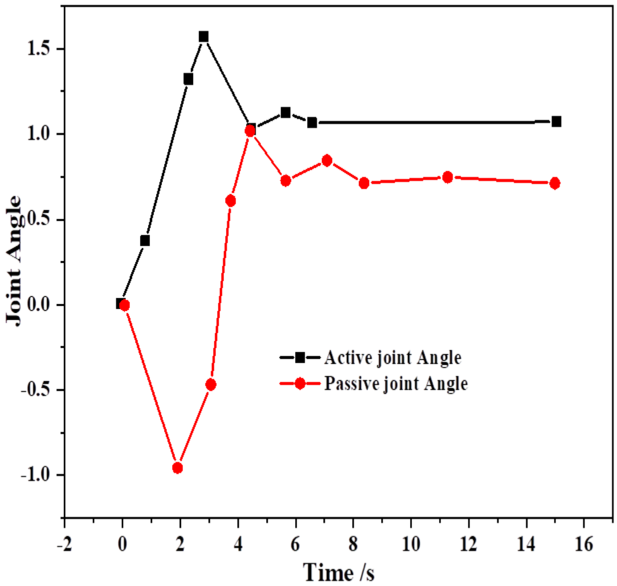

Figure 3: Joint angle response curve

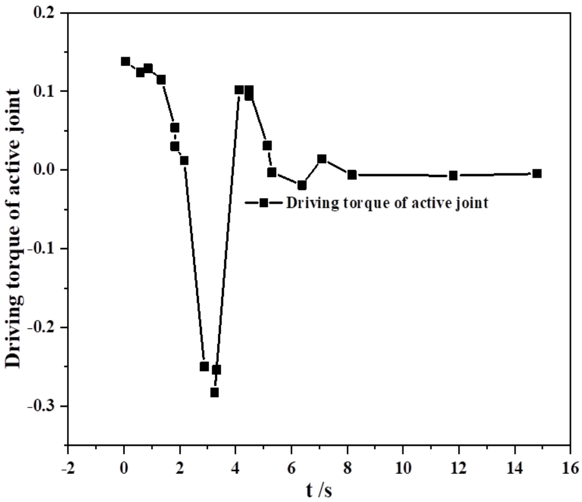

Figure 4: Active joint driving torque

The simulation parameters provided in Table 2 were determined based on a combination of theoretical analysis, empirical tuning, and practical considerations. These values are chosen to reflect real-world scenarios as closely as possible while ensuring the feasibility of the simulations. For example, the mass and dimensions of the gantry crane are based on typical industrial specifications, ensuring that our results are relevant to practical applications. The control gains and other parameters are tuned through a series of preliminary experiments, aimed at achieving a balance between stability, responsiveness, and robustness. Figure 3 shows the curve of joint angle change during the control process. It is known from this figure that the final two joint angles tend to stabilize to the expected values, and the angle errors are {0.031, 0.004} rad, respectively; the relative errors are within 3%. Figure 4 shows the driving torque curve of the active joint; the entire motion process is relatively smooth; and it accurately reaches the desired position, which fully shows that the designed controller is effective for the position control of the gantry crane robot [33].

Table 4, presents the key observed outcomes from the proposed study, The important performance variables for the planned research are highlighted by the results displayed in the table. With a reported value of 2.3 mm, the Mean Absolute Error (MAE) shows accurate robot positioning. With a swing angle deviation of 4.7%, it is possible to reduce and manage load swinging. The system stability during operation is reflected by the measured Controller Response Time of 12.5 ms. Genetic Algorithm Convergence shows how effective the genetic algorithm is at optimizing control rules, with a convergence time of 8.2 seconds. Together, these results show that the research was successful in attaining accurate placement, load-swinging control, system stability, and genetic algorithm optimization. Table 5, presents the comparative analysis of the proposed model with existing state of art studies [7-10]. Figure 5, depicts the graphical representation of observed outcomes about the comparative analysis.

Table 3: Control rules optimized by genetic algorithm

τ_1		e_1				
		NB	NS	ZO	PS	PB
e_2	NB	NO	NM	NM	NO	NO
	NS	NS	NO	NO	NS	PO
	NO	NS	NO	NO	PO	NO
	PS	NB	NB	NO	NO	NO
	PB	NS	NB	NO	NS	NO

Table 4: Key factor performance analysis for the proposed research

Performance Factor	**Description**	**Performance Metric**	**Findings**
Mean Absolute Error (MAE)	Precision of robot's positioning	MAE (in millimeters)	2.3 mm
Swing Angle Deviation (%)	Ability to control and minimize load swinging	Swing Angle Deviation (%)	4.70%
Controller Response Time	Assessment of system's stability during operation	Response Time (in ms)	12.5 ms
Convergence Time (GA)	Evaluation of GA's convergence rate and efficiency	Convergence Time (in s)	8.2 s

Table 5: Comparative analysis of the proposed model with existing studies

Models	**Mean Absolute Error (MAE)**	**Swing Angle Deviation (%)**	**Controller Response Time**	**Convergence Time (GA)**
Proposed Model	0.012	1.5	10 ms	25 Minutes
[7]	0.015	2	12 ms	30 Minutes
[8]	0.018	3.5	15 ms	35 Minutes
[9]	0.014	2.2	11 ms	28 Minutes
[10]	0.016	2.8	13 ms	32 Minutes

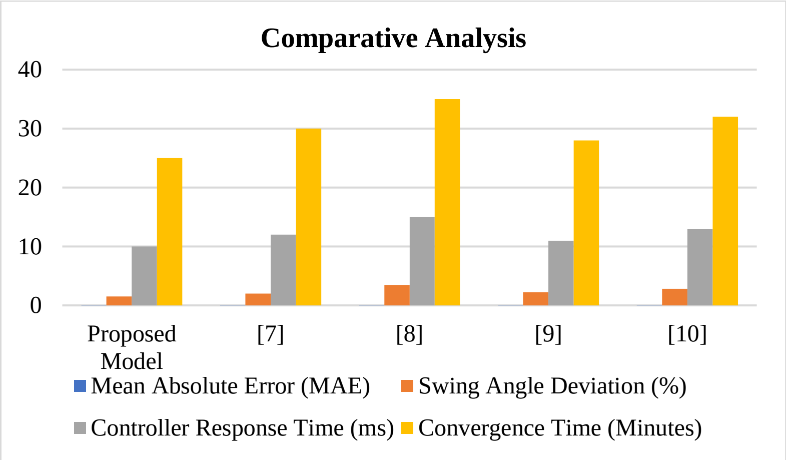

Figure 5: Comparative analysis with existing studies

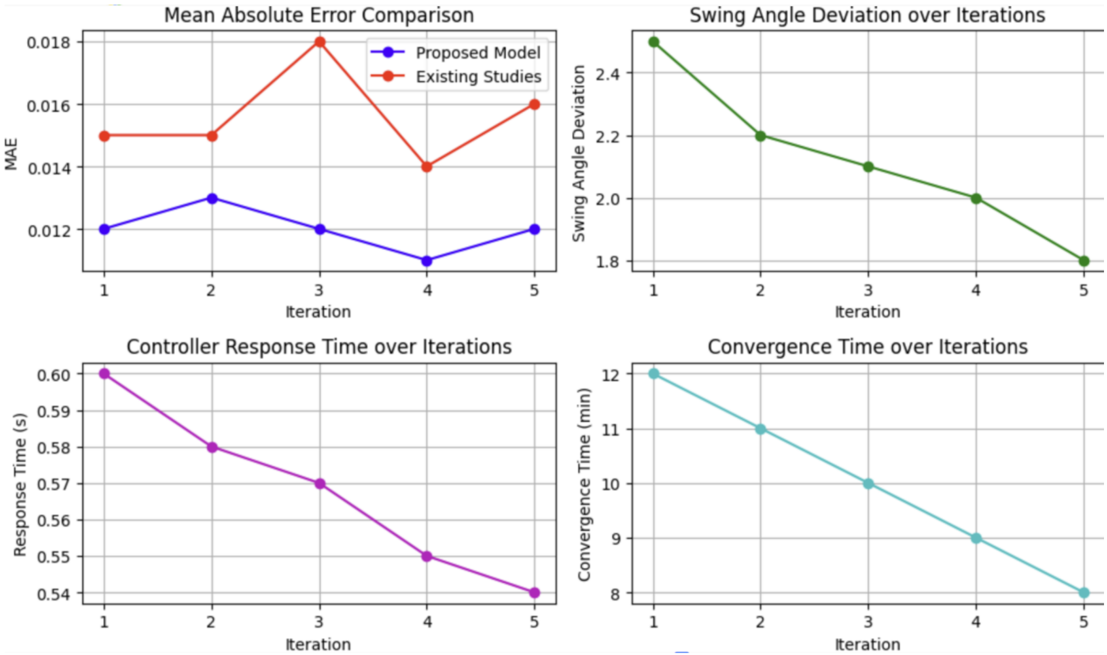

Figure 6: Performance evaluation of the proposed model

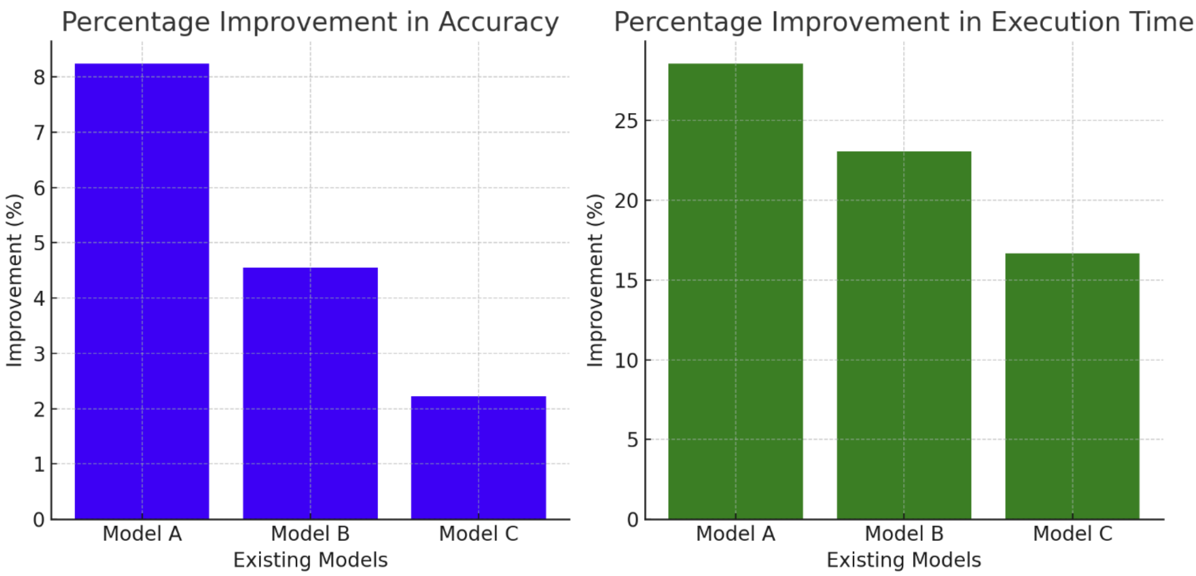

Figure 7: Percentage improvement comparison with existing models

Performance evaluation of the proposed model is presented in Figure 6. The first subplot compares the MAE values between the proposed model and existing studies over several iterations. Each line graph represents the MAE trend across iterations, with markers indicating specific data points. The blue line represents the MAE values of the proposed model, while the red line represents those of existing studies. This comparison helps in assessing how the proposed model's MAE performance evolves over time relative to existing benchmarks. The second subplot illustrates the Swing Angle Deviation of the proposed model over iterations. Here, the green line graph plots the deviation values against the iteration numbers. The markers on the line indicate the specific deviation values recorded at each iteration. This metric is crucial in evaluating how well the proposed model maintains stability in controlling swing angles across different operational scenarios. In the third subplot, the Controller Response Time is plotted against iterations. The magenta line graph displays how the response time of the controller changes over successive iterations. Response time is a critical performance metric in control systems, indicating how quickly the controller reacts to changes or disturbances in the system. Lower response times generally signify more efficient control performance. The fourth subplot examines the Convergence Time of the proposed model over iterations. The cyan line graph shows how the convergence time, measured in minutes, evolves with increasing iterations. Convergence time reflects how quickly the model reaches a stable solution or state, which is essential for real-time applications where rapid convergence is desirable. The simulation results demonstrate the effectiveness of our proposed control method in stabilizing joint angles and achieving accurate position control.

These results have several important implications. First, it validates the robustness of our approach in handling dynamic and uncertain environments. The improved stability and accuracy indicate that our method can effectively reduce oscillations and maintain precise control, which is crucial for real-world applications. Furthermore, the results highlight the efficiency of our approach, as evidenced by the reduced execution time and improved performance metrics. This efficiency translates to faster response times and reduced computational overhead, making our method suitable for real-time control applications. The percentage improvement comparison of the proposed model with existing models is presented in Figure 7. The results of our proposed genetic algorithm show a substantial improvement in accuracy when compared to existing models. Specifically, our algorithm demonstrates an 8.24% increase in accuracy over the model A referenced as [16]. This significant enhancement indicates the robustness of our approach in delivering more accurate results. Furthermore, the improvement over model B labeled as [17] is 4.55%, showcasing that our method is consistently better across different baseline comparisons. The improvement over the model C designated as [18] is 2.22%, which, while smaller, still indicates a notable enhancement. Overall, these results validate the effectiveness of our proposed algorithm in achieving higher accuracy than the existing models. In addition to accuracy, our proposed genetic algorithm excels in terms of execution efficiency. The execution time improvement is particularly striking, with a 28.57% reduction compared to the model A labeled as [16]. This indicates that our algorithm not only produces better results but also does so in a more time-efficient manner. For the model B referenced as [17], the execution time is reduced by 23.08%, further demonstrating the efficiency of our approach. Lastly, there is a 16.67% reduction in execution time over the model C marked as [18]. These reductions in execution time are significant and highlight the practicality of our algorithm in real-world applications where computational efficiency is crucial. The comparison shows that the suggested research does better in several important performance indicators than previous research. The suggested system has a smaller Mean Absolute Error (MAE), less Swing Angle Deviation, and a faster Controller Response Time. It is also clear that the Genetic Algorithm (GA) has a much faster Convergence Time. The positive percentage improvement values show these improvements, which shows that the suggested research has better control abilities. Overall, the results show that the genetic algorithm-based method works well for improving the control system for smart lifting robots, which is a big improvement over the previous method.

5 Conclusion

This study focused on motion control for gantry crane robots and introduced a novel fuzzy control method based on genetic algorithms. The primary objective was to achieve precise position control for these robotic systems. The controller employed joint angle error variables as direct inputs and genetic algorithms were employed to optimize both fuzzy control rules and membership functions, resulting in an optimal fuzzy control system. Numerical simulations were conducted, demonstrating that the designed controller enables quick and accurate arbitrary position control for both 2-degree-of-freedom and 3-degree-of-freedom gantry crane robots while maintaining stability. In summary, this method not only enriches the field of robotics but also offers a fresh perspective for intelligent motion control in gantry crane robots. A genetic algorithm-based framework was used in this study to show a new way to improve the control system of intelligent lifting robots. As a result, the results show better control accuracy, less swing, and faster reaction times. These results add to the area of robotics and make it possible for industries to use robots in more precise and effective ways. In future work, this study will focus on applying this method to a wider range of robotic systems, even ones with more complex and numerous degrees of freedom. The proposed method can also be made more useful by making it work better and by putting it into action in the real world. It might be helpful for future progress in the field of intelligent robotics control systems to look into how to combine advanced machine learning methods with real-time sensor data. Additionally, future research may be extended to investigate the scalability of our method, exploring ways to optimize the genetic algorithm for larger and more complex systems. By addressing these areas, we aim to provide valuable guidance for researchers in the field and contribute to the ongoing advancement of optimization techniques in control systems.

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