Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 14, No. 2, 2024

Optimization Study of Nonlinear Fuzzy Control System Based on Accelerated Evolutionary Programming

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Abstract: The objective of this study is to enhance the responsiveness and precision of control systems through the acceleration of evolutionary programming in the optimization of nonlinear fuzzy control systems. Nonlinear systems are ubiquitous in engineering practice, presenting significant challenges due to their complexity and uncertainty for traditional control methodologies. Fuzzy control, an intelligent control approach rooted in empirical rules, possesses the capability to navigate uncertain and nonlinear issues. However, conventional fuzzy controllers struggle to achieve optimal control performance when confronted with highly complex nonlinear systems. Consequently, this paper introduces the application of accelerated evolutionary programming (RGA) for the optimization of fuzzy controllers, aiming to augment their performance in nonlinear systems. By merging genetic algorithms with a fuzzy adaptive PID controller, the optimized fuzzy controller is better equipped to adapt to the dynamic changes of nonlinear systems, offering robust and efficient control strategies. The results of simulation experiments demonstrate a marked improvement in response time, stability, and error reduction with the fuzzy control system based on RGA optimization. This study offers novel insights and methodologies for the further optimization of control within nonlinear systems, while providing theoretical support for the practical applications of complex systems.

Keywords: Accelerated evolutionary programming; Nonlinear; Fuzzy control systems; Optimization studies.

1. Introduction

As modern industrial systems become increasingly intricate, control systems face formidable challenges in managing nonlinearity, time-variance, and uncertainty. Traditional linear control methods often struggle to address the nonlinear characteristics inherent in such complex systems. Fuzzy control, an intelligent control method based on fuzzy logic reasoning, has gained widespread application in nonlinear system control due to its independence from precise mathematical models and its capability to handle vagueness and uncertainty. Nevertheless, despite its advantages, fuzzy control still encounters the need for performance optimization in complex nonlinear systems. Consequently, optimizing the design of fuzzy controllers has emerged as a crucial research area. Accelerated Evolutionary Programming, an optimization method rooted in evolutionary algorithms, can swiftly identify optimal solutions for systems by simulating natural evolutionary processes. This paper aims to explore optimization techniques for nonlinear fuzzy control systems based on Accelerated Evolutionary Programming, with the goal of enhancing the response speed and control accuracy of fuzzy control systems when addressing complex nonlinear issues, thereby providing effective solutions for nonlinear system control in practical engineering applications.

2. Accelerated Evolutionary Programming Algorithms

Accelerated Evolutionary Programming (AEP), as an enhanced form of evolutionary algorithm, seeks to address the challenges of efficiency and global search capability in solving complex nonlinear optimization problems by introducing innovative parameter designs. Traditional evolutionary programming algorithms often encounter issues such as slow convergence and a tendency to become trapped in local optima. To overcome these limitations, AEP significantly improves algorithm performance by incorporating two crucial parameters: directional information and age information. The directional information parameter, represented by binary values of +1 and -1, indicates the adjustment direction of chromosome parameters, thereby making the search process more precise and efficient. Age information, another key parameter, regulates the lifespan of chromosomes during the evolutionary process, thereby controlling the breadth of the population's search and ensuring that the algorithm effectively escapes local optima while maintaining global search capability. The introduction of these parameters endows AEP with enhanced adaptability and robustness in addressing complex optimization problems [1].

To further quantify the performance of AEP, it is typically assessed using two core metrics. The first of these is the Convergence Speed (CS) metric, which measures the efficiency with which the algorithm approaches the global optimum within a limited number of iterations. This is specifically illustrated in Equation (1):

$$CS = \frac{1}{T}\sum_{t=1}^{T}\frac{f(x_{best}(t)) - f(x_{opt})}{f(x_{opt})} \quad (1)$$

where T represents the total number of iterations,f(xbest(t)) denotes the optimal solution in the tth iteration, and f(xopt) is the known global optimal solution. This index visualizes the convergence efficiency of the algorithm by counting the gap between the optimal solution in each iteration and the global optimal solution.

The second is the algorithm stability index (Stability Index, SI), which is used to evaluate the stability of individual fitness and the diversity of the population of the algorithm in the evolutionary process. The index is shown in Equation (2):

$$SI = \frac{\sqrt{\sum_{i=1}^{N}(f(x_i) - f_{avg})^2 / N}}{f_{avg}} \quad (2)$$

where N is the population size f(xi) is the fitness value of the ith individual and favg denotes the average fitness of the population. This metric evaluates the stability of the algorithm and the diversity of the population by measuring the degree of discretization of individual fitness.

With the evaluation of these two core metrics, the accelerated evolutionary programming algorithm demonstrates its significant advantages in dealing with nonlinear, complex multimodal problems. The guidance of direction information and the regulation of age information enable the algorithm not only to quickly approximate the global optimal solution, but also to maintain high stability and adaptability in the diverse solution space. The improvement of this algorithm not only provides strong theoretical support, but also achieves remarkable results in practical applications, especially in the control and optimal design of complex industrial systems. The accelerated evolutionary programming algorithm has become an important tool in the optimization of nonlinear fuzzy control systems through these innovative designs [2].

3. Overview of Nonlinear Fuzzy Control Systems

3.1. Characteristics and Challenges of Nonlinear Systems

The characteristics of nonlinear systems render them particularly challenging in practical applications, as these systems often exhibit intricate dynamical behaviors, including multiple equilibrium points, singularities, periodicity, and chaos. Such traits arise from the nonlinear interactions between the internal state variables of the system, as well as the complex effects of external disturbances on system responses. Traditional linear methods are inadequate for effectively modeling and analyzing nonlinear systems, presenting significant difficulties for control design. Linear control theory typically relies on the assumption of system linearization, which may be valid for responses within a limited range but often fails when addressing the global dynamics of the system. Additionally, the models of nonlinear systems are usually highly complex, containing numerous nonlinear equations that are challenging to describe accurately, making system analysis and control design more arduous. Fuzzy control, as an intelligent control method for handling uncertainty and complex systems, offers a novel approach by combining empirical rules with fuzzy logic for the control of nonlinear systems [3]. However, fuzzy control systems still face dual challenges of control precision and response speed when dealing with highly pronounced nonlinear features in complex systems. Specifically, the design of fuzzy controllers depends on the completeness of the rule base and the reasonableness of the membership functions, which directly impact the system's control performance. Addressing the complexity and diversity of nonlinear systems requires a deep understanding of their nonlinear behaviors and the use of adaptive and optimization algorithms to enhance the robustness and adaptability of the control system. Thus, research into nonlinear fuzzy control systems holds significant theoretical and practical importance, challenging the boundaries of traditional control theory while offering powerful solutions to the control problems of complex systems in the real world.

3.2. Fuzzy Control Principles

As an effective method to deal with uncertainty and complex systems, the core principle of fuzzy control is based on the theory of fuzzy logic, by introducing fuzzy sets and fuzzy reasoning into the control process, so as to realize effective control of complex systems in the absence of precise mathematical models. The block diagram of the principle of fuzzy control is shown in Figure 1, and the basic mechanism of fuzzy control can be simplified and expressed as shown in Figure 2, which is also the basic structure diagram of fuzzy control system.

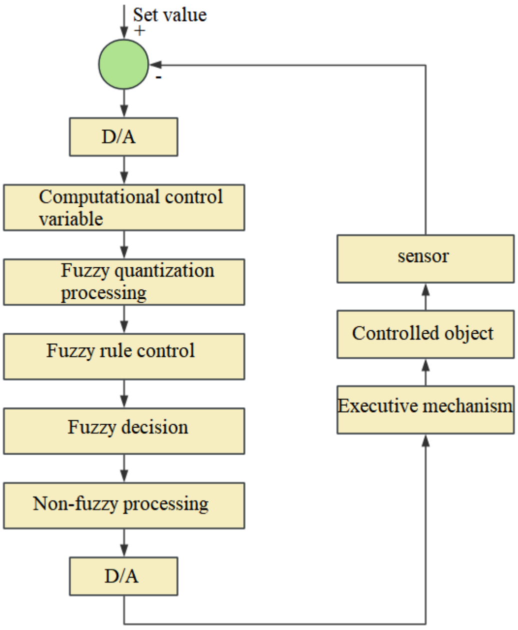

Figure 1. Block diagram of fuzzy control principle

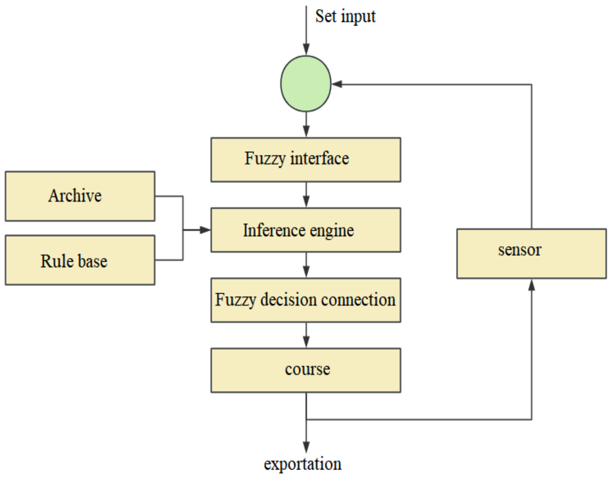

Figure 2. Basic structure of fuzzy control system

Fuzzy control systems can be categorized into univariate and multivariate control systems based on the number of input and output variables. Its structure is shown in Figure 3.

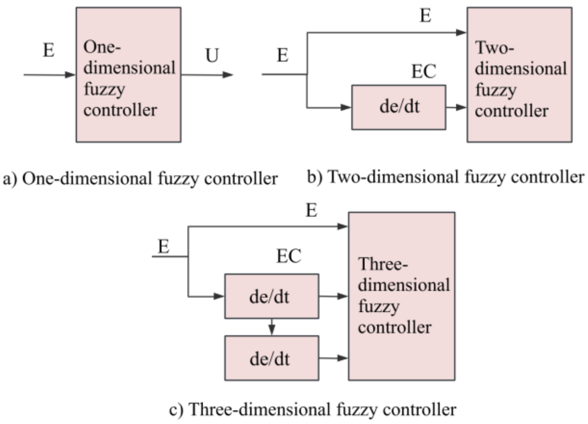

Figure 3. fuzzy control system architecture

In a one-dimensional fuzzy control system, typically only a single input variable is involved, resulting in a relatively simple control strategy. However, due to its reliance on a singular deviation value, it fails to fully capture the system's dynamic behavior and varying characteristics, leading to limited effectiveness in controlling complex nonlinear systems [4].

Two-dimensional fuzzy controllers are widely utilized, introducing two input variables: error (E) and rate of change of error (EC). This design better reflects the dynamic characteristics of the system output, significantly enhancing control precision and system responsiveness, and thus finds extensive application in industrial control and engineering practice.

Three-dimensional fuzzy controllers extend the traditional two-dimensional controllers by incorporating the rate of change of error (ECC) as a third input variable. This extension allows the controller to more accurately capture system errors and their trends, making it particularly suitable for nonlinear systems with complex dynamic characteristics. The structure of the three-dimensional fuzzy controller considers the interrelationships among system error (E), error change (EC), and rate of change of error (ECC), providing a more refined control output through a more intricate fuzzy reasoning mechanism. Consequently, three-dimensional fuzzy controllers effectively address the control needs of multivariable complex systems and demonstrate exceptional performance in dealing with nonlinearity, time-variation, and model uncertainty [5].

The advantage of fuzzy control lies in its independence from precise mathematical models of the system. By combining fuzzy reasoning with rules, it can make reasonable control decisions in highly uncertain environments. Its core concept is to transform complex nonlinear control problems into a series of simplified control rules through fuzzy logic processing and approximate reasoning. This method is particularly suited for controlling complex systems that cannot be precisely modeled, such as nonlinear systems, time-variant systems, and systems with uncertainty and noise disturbances. With the deepening of research and the expansion of applications, the integration of fuzzy control with other intelligent algorithms (such as neural networks and genetic algorithms) continues to advance, further enhancing the potential of fuzzy control systems in addressing complex nonlinear control challenges.

4. Optimization design of fuzzy controller based on RGA

4.1. Genetic Algorithm

4.1.1. Principle of Genetic Algorithm

The Genetic Algorithm (GA), as an optimization technique emulating the process of natural selection, draws upon mechanisms such as inheritance, mutation, selection, and crossover found in biological evolution. It offers a potent method for tackling intricate optimization challenges (as depicted in Figure 4). The fundamental process of the Genetic Algorithm can be distilled into steps: population initialization, fitness evaluation, selection, crossover, mutation, and population update. The algorithm generates an initial population either randomly or based on experience, with each individual representing a potential solution encoded in the form of chromosomes. The fitness function assesses the quality of individuals, measuring their adaptability within the solution space according to specific criteria, and is typically defined as the optimization objective function, such as f(x), which indicates the quality of the current solution [6].

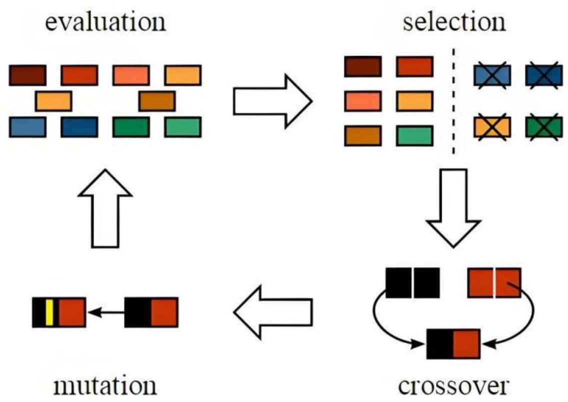

Figure 4. Principle of genetic algorithm

The selection operation is based on the results of the fitness function, which selects individuals with higher fitness into the next generation. Common selection methods include Roulette Wheel Selection (RWS) and Tournament Selection (TSS), in which the selection probability Pi is usually proportional to the fitness value fi in RWS, expressed as shown in Equation (3):

$$P_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{3}$$

Crossover operations, on the other hand, mimic the process of genetic recombination in biological inheritance, in which new individuals are created by exchanging some of the genes of two or more individuals. After the crossover operation, the new individuals inherit some of the characteristics of the parent individuals, which is manifested as an increase in population diversity [7]. Common crossover methods include single-point crossover, multipoint crossover and uniform crossover, and the operation of single-point crossover is expressed in Equation (4):

$$\begin{aligned} C_1 &= (P_1[1:k], P_2[k+1:n]) \\ C_2 &= (P_2[1:k], P_1[k+1:n]) \end{aligned} \tag{4}$$

where P1 and P2 are parent individuals, C1 and C2 are offspring individuals, and k is the crossover point.

The mutation operation introduces a small probability of random changes in chromosomal genes, which increases the diversity of the population and provides the possibility for the algorithm to jump out of the local optimum. The mutation operation often uses a randomly selected gene position in the chromosome and inverts or randomly changes its value, and its probability of mutation P_m is usually set small to ensure the stability of the algorithm.

In the process of population renewal, the new generation of individuals is screened based on the fitness value, and the good individuals will survive and enter the next generation cycle. The genetic algorithm gradually approaches the global optimal solution by repeatedly performing the above steps. Its termination condition can be to reach a predetermined number of generations or stop when the change of fitness value tends to stabilize [8].

In summary, the genetic algorithm flow is shown in Figure 5:

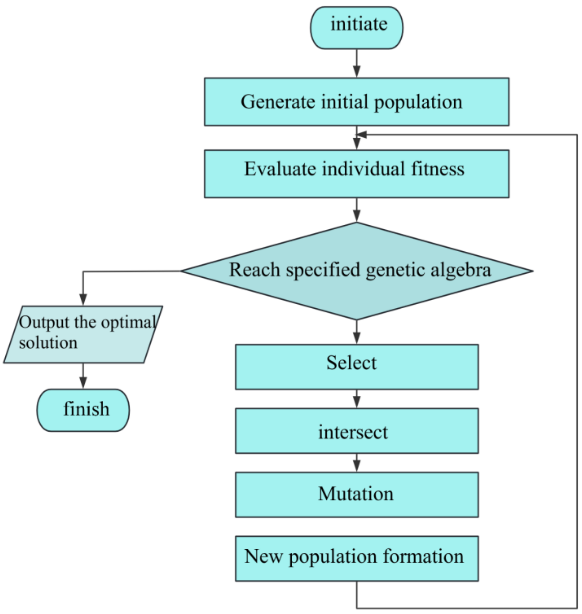

Figure 5. Genetic Algorithm Flow

The core of genetic algorithm lies in the design of its fitness function and the reasonable setting of crossover and mutation operations. In the optimization design of fuzzy controllers, genetic algorithms are widely used in the optimization search process to optimize the performance of fuzzy controllers by adjusting the parameters of fuzzy rules or the affiliation function. The genetic algorithm shows strong robustness and adaptability when dealing with multivariate complex optimization problems, and provides an effective solution for the optimization design of nonlinear fuzzy control systems.

4.1.2. Design of fuzzy adaptive controller

The design of a fuzzy adaptive PID controller represents a sophisticated control strategy that amalgamates fuzzy logic with traditional PID control, aimed at overcoming the limitations inherent in a singular PID controller when addressing nonlinear and time-variant systems. By incorporating a fuzzy inference mechanism, this controller enables dynamic adjustment of PID parameters, thereby enhancing system control performance and robustness, as illustrated in Figure 6 of the fuzzy adaptive PID controller. The crux of the design process lies in the development of an appropriate fuzzy rule base and the selection of suitable membership functions. Typically, fuzzy inference systems utilize error e and rate of change of error ec as input variables, with the output being the adjustment quantities for the PID controller's three parameters: K_p, K_i, and K_d. Formulating fuzzy rules requires a comprehensive consideration of the system's dynamic characteristics and expert knowledge to ensure adaptability to varying operating conditions. The choice of membership functions, such as triangular, trapezoidal, and Gaussian, directly affects the accuracy of fuzzification and defuzzification processes. In practical applications, real-time performance and computational complexity must also be considered to balance control efficacy with system resource consumption. The RGA-based optimization method can further enhance the performance of the fuzzy adaptive PID controller by optimizing fuzzy rules, membership function parameters, and initial PID values, achieving a global optimization design of the controller. This integration of genetic algorithms and fuzzy adaptive PID provides an effective solution for complex industrial process control [9].

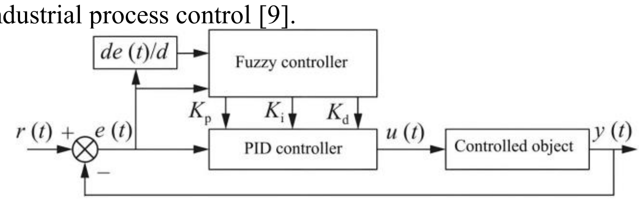

Figure 6. Fuzzy adaptive PID controller

4.2. Optimization of RGA-based fuzzy controller

The optimization design of a fuzzy controller based on Real-valued Genetic Algorithm (RGA) constitutes an advanced approach that merges intelligent optimization with the theoretical framework of fuzzy control. This methodology adeptly addresses the challenges associated with parameter tuning in traditional fuzzy controller design, leveraging the global search capabilities of RGA. During the optimization process, key parameters of the controller are encoded as real-valued chromosomes, encompassing membership function parameters, fuzzy rule weights, and more. The design of the fitness function is paramount, typically involving a weighted sum of system performance indicators such as overshoot, steady-state error, and settling time as evaluative criteria. The selection operation within RGA employs an elitism preservation strategy, ensuring that superior individuals propagate to subsequent generations. The crossover operation utilizes an arithmetic crossover method, producing new chromosomes through linear combinations of parental chromosomes, thereby enhancing the continuity of the search space. Furthermore, mutation introduces Gaussian perturbations, maintaining population diversity and preventing convergence to local optima. Throughout the optimization process, RGA iteratively evolves the parameters of the fuzzy controller until termination conditions are satisfied. This approach is particularly advantageous as it automates the optimization of complex multi-input multi-output fuzzy systems, exhibiting a robust adaptability, especially suited for controlling nonlinear and time-varying systems. Nonetheless, the computational complexity of RGA is considerable, necessitating a balance between optimization efficacy and computational time in real-time control applications. By integrating the adaptive capabilities of fuzzy control with the global optimization characteristics of RGA, this methodology offers a powerful design tool for managing complex industrial processes.

5. Simulation experiment and result analysis

5.1. Experimental setup and parameter selection

In the simulation experiment of complex control system, the experimental setup and parameter selection are important steps to ensure the dynamic performance and stability of the system, which directly affect the optimization effect of the whole control strategy. In the process of experimental setup, the initial parameter selection of the controller is based on the mathematical model of the controlled object. For a typical second-order system, its transfer function is usually expressed as shown in Equation (5):

$$G(s) = \frac{\omega_n^2}{s^2 + 2\varsigma\omega_n s + \omega_n^2} \quad (5)$$

where ω_n is the natural frequency of the system and ς is the damping ratio. In order to further improve the response speed and steady-state accuracy of the controller, the experiment also involves the parameter settings of the optimization algorithm, such as the population size, the crossover probability and the variance probability, and the selection of these parameters needs to be adjusted through multiple simulation experiments to avoid overfitting or inefficient search. During the experimental process, by setting different initial conditions and interference terms, the performance of the controller can be tested under a variety of working conditions, so as to verify its robustness and adaptability. Ultimately, the collection and analysis of the experimental data will provide an important basis for further optimization of the controller parameters and ensure the reliability and repeatability of the experimental results [10].

5.2. Algorithm Performance Evaluation

Algorithm performance evaluation is an important part to verify the effectiveness and superiority of the designed control strategy. In the evaluation process, the algorithm is comprehensively analyzed by several performance indicators to ensure its stability and robustness under different operating conditions. Commonly used performance indicators include steady state error, overshoot, rise time and regulation time. These metrics can reflect the rapidity, accuracy and stability of the control system. In this study, simulation experiments are conducted to verify the performance of the proposed fuzzy adaptive PID controller through different test cases. Table 1 summarizes the comparison of the performance metrics of different algorithms under typical test cases.

Table 1. Comparison of performance metrics of different algorithms under typical test cases

Algorithm type	Steady state error ess	Overshoot Mp	Rise time tr(s)	Adjusting time ts(s)
Conventional PID controller	0.015	20.5%	1.2	4.8
Fuzzy PID controller	0.010	15.2%	1.0	4.2
Fuzzy controller based on RGA optimization	0.005	10.1%	0.8	3.6

As can be seen from the data in the table, the fuzzy controller based on accelerated evolutionary programming significantly outperforms the traditional PID controller and the basic fuzzy controller in all performance indicators. Specifically, the optimization algorithm significantly reduces the steady-state error, reduces the overshoot of the system, and shortens the rise time and regulation time of the system. These improvements indicate that accelerated evolutionary programming can effectively enhance the dynamic response characteristics and stability of the control system, thus adapting to more complex nonlinear control tasks. These results not only verify the effectiveness of accelerated evolutionary programming in fuzzy control system optimization, but also lay a solid foundation for further research and practical applications.

6. Conclusion

This study has optimized the design of nonlinear fuzzy control systems by introducing accelerated evolutionary programming, demonstrating the effectiveness of this method in enhancing system performance. In the face of the challenges posed by the complexity and uncertainty of nonlinear systems, the optimized fuzzy controller exhibits superior robustness and adaptability. Simulation results reveal that the RGA-based fuzzy controller significantly improves response speed, system stability, and error control, confirming the potential of this optimization method for practical applications. This research not only offers new optimization insights for controlling complex nonlinear systems but also lays a foundation for further exploration into the optimization and application of intelligent control algorithms. Future research should delve into the integration of accelerated evolutionary programming with other intelligent algorithms to enhance the performance of control systems in more complex environments.

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