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Genetic Algorithm-Based Mach Number Control of Multi-Mode Wind Tunnel Flow Fields

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Abstract: There are unfavorable conditions such as constantly changing working conditions and frequent disturbances that affect Mach number control in wind tunnel flow fields. As the proportional, integral and differential (PID) parameters need to be re-tuned for each working conditions of a wind tunnel, the operational costs of wind tunnels are very high. Therefore, to lower these costs, a genetic algorithm was utilized to tune the PID parameters to achieve Mach number control of a multi-mode wind tunnel flow field. In this paper, firstly, models for the multi-mode wind tunnel were established; secondly, a PID control system was designed based on the genetic algorithm and the control effects of the proposed PID control system were verified by simulations and were compared with the effects of a PSO tuning PID control system.

Keywords: wind tunnel; Mach number control; multi-mode; genetic algorithm; PID

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1. Introduction

Wind tunnels, also known as wind tunnel laboratories, are one of the commonly used pieces of experimental equipment in the field of aerospace. As it is too expensive to directly test aircraft models under actual conditions, people usually choose to conduct model tests in wind tunnel equipment before finally testing the mock-up in a real-life environment. According to the principle of dynamic similarity and the relativity principle of motion, aircraft cannot directly fly in the wind tunnel flow field; so, it is necessary to change the blowing speed to simulate the actual flight environment by fixing the aircraft model [1]. Therefore, wind tunnel tests of models play a vital role in the developmental process of aviation aircraft. With the continuous development of science and technology in the field of aerospace, the design theory of aircraft is continually updated, and the structures of aircraft are also constantly iterated—which is bound to increase wind tunnel tests linked to the development and production of these aircraft and to lead to higher requirements for the performance of wind tunnel simulation control. The Mach number is an important parameter in wind tunnel flow fields. The effect of Mach number control directly affects the quality of the wind tunnel flow field, and even affects the selection design of the aircraft. The performance indexes of Mach numbers include speed, continuity, precision, etc. The analysis of and research into Mach number control of multi-mode wind tunnels could bring more scope for improvements in the design of and research into aircraft; in addition, it could also reduce the energy consumed by wind tunnel blowing tests. Therefore, the topic of Mach number control in multi-mode wind tunnel flow fields will remain a hot topic in the coming period of time. Since wind tunnel flow fields are complex nonlinear, multivariable systems—with interferences such as lag, coupling, and time variation—there are many difficulties to overcome for the precise control of Mach numbers. Additionally, due to the influence of the wind tunnel size and structure and the differences between mathematical models for the multiple modes of wind tunnels, how to accurately establish a wind tunnel flow field model is a significant problem. For each new wind tunnel, it is necessary to accurately establish a wind tunnel flow field model; a wind tunnel device is an energy-consuming instrument—of which the single-use operational cost is more than tens of thousands of yuan—that is unable to achieve a fast performance and wastes time and energy. One study found that there are process similarities between multiple modes of wind tunnels. If the historical data on existing wind tunnels and established wind tunnel historical models are combined with the new mode characteristics of wind tunnels to establish a new model, it will obviously bring more advantages in terms of saving time and resources.

As a key piece of equipment in the development of the aerospace industry, wind tunnels have always been a hot spot of scientific research. With the rapid development of science and technology, people increasingly require high performance and low energy consumption in aviation aircraft, which requires the control of wind tunnel flow field Mach numbers to achieve a certain precision. From the perspective of the Mach number control of wind tunnel flow fields, Yi, F., et al. applied iterative learning to the Mach number control of a wind tunnel to obtain an accurate attitude angle compensation model [2]. Jin, Z. W., et al. designed a predictive control strategy based on a neural network model, applied it to the real-time control of a 2.4 m wind tunnel flow field, and obtained an effect that was significantly better than a traditional PID controller [3]. Yang, S. W. proposed a generalized predictive control method for the Mach number of wind tunnel flow fields that can achieve fast and high-precision control in industrial processes [4]. Ju, X. F. designed a predictive control for multi-model wind tunnel fields based on multiple models [5]. Gao, H., et al. proposed a feedforward controller based on the combination of Gaussian process regression with traditional PID control to improve Mach number control accuracy [6]. Lian, X. F. used a genetic algorithm (GA) to optimize the structure of a BP neural network and established a prediction model for wind tunnel flow fields [7]. Cameron, R. N., et al. applied a GA to optimize a controller on a neural network model of wind tunnels [8].

It can be seen from the analysis above that the control of Mach numbers has always been a very important part of the wind tunnel-related research field. PID control, as a traditional control method, is widely used in the Mach number control of wind tunnel flow fields. Additionally, as a stochastic search optimization algorithm, GAs are feasible for optimizing the control parameters of controllers. Using the optimization ability and good adaptive ability of GAs, a wind tunnel flow field Mach number controller with a good control effect can be designed. Therefore, in this paper, a GA was utilized to tune the PID parameters to achieve the Mach number control of a multi-mode wind tunnel flow field. This started from the system structure of the GA tuning PID control; then, the modeling strategy of the multi-mode wind tunnel flow field was introduced. Then, based on the analysis of the characteristics of the wind tunnel flow field, a Mach number control strategy based on the GA was established, and a complete genetic algorithm [9] tuning PID control system was designed. Finally, a simulation experiment was conducted to verify its control effect and was compared with the particle swarm optimization (PSO) [10] algorithm to verify the superiority of the GA tuning PID controller.

The remaining work of this paper included the following aspects: Firstly, in the Section 2, the Mach number PID control system of the wind tunnel flow field is introduced—including a brief introduction of the structure of the GA tuning PID control system, the modeling strategy for the multi-mode wind tunnel flow field, and the design of the GA subfunction. Then, in Section 3, the wind tunnel system is described in detail, the models for the multi-mode wind tunnel Mach number are established, and the GA tuning PID control of the Mach number is conducted for multiple modes. Finally, the conclusions are drawn in the Section 4.

2. Methodology

2.1. GA Tuning PID Control System

This paper selected a complete GA tuning PID control system from Simulink. The idea was to determine the parameters of the GA and then input them into the PID controller to directly control the wind tunnel system model. The whole system was a closed-loop feedback control system. According to the above ideas, the following system was constructed, as shown in Figure 1:

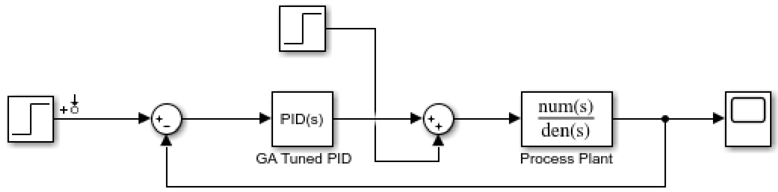

Figure 1. GA tuning PID control system of the wind tunnel flow field.

In this system, the given input is a unit step input, since the step signal is a representative input for the system; if the step input system can have a good control effect, then the system can also run well for other inputs. In addition, after 10 s of the system operation, one unit step disturbance is added to observe the anti-interference performance of the controller for the step disturbance. The controlled plant was the wind tunnel model. As the multi-mode wind tunnel flow field had different wind tunnel models corresponding to different given Mach numbers, multiple simulation experiments were conducted for different wind tunnel models.

2.2. Modeling of the Multi-Mode Wind Tunnel Field

In order to meet the need for Mach number control under the test conditions, an accurate wind tunnel model had to be established.

A data modeling method was used to model the input and output of the system. The basic process of the data modeling method was to add a test signal to the system to record the output response of the system; then, the system was modeled with appropriate mathematical methods according to the input and output data and optimized continuously—so as to get a model more suitable for the actual conditions of the system.

Since different wind tunnel modes will have different flow field properties, the multi-mode modeling method was chosen to better describe the transfer function of the wind tunnel flow field. The system identification method was used to obtain the Mach number transfer function model in the flow field of the multi-mode wind tunnel. The input data used in this paper was the expected Mach number. The output data was the Mach number calculated by measuring the actual data on the total pressure and static pressure using Equation (1):

$$Ma = \sqrt{5[(\frac{P_0}{P_s})^{\frac{2}{7}} - 1]} \tag{1}$$

2.3. Design of the GA Subfunction

Genetic algorithms are based on the theory of natural selection and Mendelian genetics and are applied to solve practical problems according to the processes of reproduction and gene mutation in nature. All the feasible solutions obtained by a GA will be adopted and encoded into a "chromosome", which is an individual in the GA. The population is made up of many individuals. The first step of a GA is to generate a random initial population, and then to calculate the respective adaptation value of all the individuals according to the fitness function; the selection operation used to generate the next generation is performed based on this adaptation value, reflecting the evolution principle. "Excellent" individuals will gain "reproduction" rights and produce the next generation, while "poor" individuals will be eliminated; then, the selection operation generates a new offspring population through cross and variation operations. Individuals in this generation of the population inherit some good traits of the parent through genetic inheritance—thus achieving a better overall performance than individuals in the parent population, which can allow the population as a whole to achieve the optimal solution.

2.3.1. Determination and Representation of Parameters

First, the range selection of the parameters k_p, k_i, and k_d needed to be determined according to the controlled plant—namely, the wind tunnel flow field model under a given Mach number. The parameters were represented as binary strings. Connecting 3 such strings yielded a final binary string that served as the operating object of the GA. In this way, the GA was able to optimize all three parameters at the same time.

2.3.2. Selection of the Initial Population

The initial population was given randomly by a computer. For binary coding, random numbers were generated between 0 and 1 and these generated numbers were rounded, where data between 0 and 0.5 represented 0 and data between 0.5 and 1 represented 1. Furthermore, the population size needed to be determined based on the computational complexity. The number of individuals in the original population should not be too small; otherwise, although the GA can work faster, the lower number of individuals can lead to a lower species diversity—which can easily cause the "precocious" phenomenon, resulting in the deterioration of the parameter optimization effect. Similarly, the population number should not be too large, otherwise the efficiency of the GA will be low.

2.3.3. Coding and Decoding

The main methods of encoding in GAs are the symbolic coding method, binary coding method, and decimal coding method—among which the most common decimal coding method is the floating point coding method. The binary encoding method was adopted in this paper, and the genotype of the individuals made up by this method was a binary string. Binary coding methods have the following advantages over other coding methods:

1. Convenient implementation of selection, crossover, and variation operations;
2. Convenient for the encoding and decoding of individuals;
3. It is easy to analyze the algorithm.

For a parameter with a value range $[U_1, U_2]$, the corresponding binary encoding length is k; assuming an individual encoding $b_k b_{k-1} \cdots b_2 b_1$, the corresponding decoding formula is:

$$X = U_1 + \left(\sum_{i=1}^{k} b_i 2^{i-1} \right) \times \frac{U_2 - U_1}{2^k - 1} \tag{2}$$

2.3.4. Determination of the Fitness Function

Fitness is an indicator for evaluating the proximity of an individual in a population to the optimal solution in a genetic algorithm, and the function representing the individual's fitness is called the fitness function.

In this paper, an error function was selected first, and the absolute error value time integral was used as the performance index. To prevent the effects of the integral saturation phenomenon on the control, the square of the input was added to the integral term. The error function was obtained as below:

$$J = \int_0^{\infty} (w_1 |e(t)| + w_2 u^2(t)) dt + w_3 \cdot t_u \tag{3}$$

where $e(t)$ is the system deviation, $u(t)$ represents the controller output, t_u represents the rise time, and w_1, w_2, w_3 are the weights.

At the same time, measures need to be taken for the possible overshoot of the step response of the wind tunnel flow field model. If the system response produces overshoot, the output change will be added into the integral term of the error function. The final error function was obtained as follows:

$$J = \int_0^{\infty} (w_1 |e(t)| + w_2 u^2(t) + w_4 |\Delta y(t)|) dt + w_3 \cdot t_u \tag{4}$$

where w_3 is the weight and $w_4 >> w_1$.

Thus, the individual fitness function was:

$$F = \frac{1}{J} \tag{5}$$

2.3.5. Selection Implementation

After the fitness function was obtained, the relative fitness of all the individuals in the population was determined. All individuals were ranked by fitness in descending order and the cumulative probability was calculated for each individual. The cumulative probability is defined as the cumulative probability of the n-th individual being the sum of the relative fitness of that individual and the cumulative probability of the ($n-1$)-th individual, where $1 \leq n \leq (M-1)$ and M is the number of populations. After calculating the cumulative probability, a random number of 0–1 is generated. If the random number is greater than the cumulative probability of the ($n-1$)-th individual and less than the cumulative probability of the n-th individual, the n-th individual is selected.

2.3.6. Crossover Implementation

Crossover is an important way of generating new individuals in GA, and the crossover probability should usually be set to large values. However, if the selection is too large, it can destroy the good shape of the population and thus negatively affect evolutionary calculations; if this value is too small, then the new biogenesis becomes slow. Generally, the interval of the crossing probability is [0.5, 0.95]. In this paper, the single-point crossover algorithm was adopted, in which a crossover point is fixed in an individual's gene sequence, and some parts of the two paired genes are exchanged according to the crossover rate.

2.3.7. Variation Implementation

Coming from gene mutations in biology, the role of the mutation operator is to reverse a position on an individual genotype in a population. The probability of variation should not be too small or too large and cannot prevent the "early maturity" phenomenon; the latter may destroy the existing, better genetic model, leading to the evolution of the random search algorithm. The variation probability is generally set to be between 0.001 and 0.1.

In this paper, a basic position variation algorithm was adopted as follows: first, the gene mutation position of an individual coding string was selected, and then the mutation probability was set; finally, the original gene was reversed according to the probability.

3. Illustration and Discussion

3.1. Process Description of the Wind Tunnel System

The structure of a wind tunnel can be divided into three parts: namely, the measurement control system, drive system, and hole body. The measurement control system can be regarded as a combination of the measuring transmission link and controller that operates according to a previously set program; it controls various components of the wind tunnel equipment, such as valves and moving components; measures the air pressure, attack angle, and related physical quantities required by instruments and other sensors; and carries out the analysis and processing of collected data. The driving system is able to generate a continuous air flow in the wind tunnel flow field, which can be regarded as the actuator in the control system. The cave body is an important part of the wind tunnel structure—including the test section, shrinkage section, nozzle, etc.—that is mainly used to guide the air flow of the wind tunnel flow field to ensure the stability of the wind tunnel flow field quality. Most wind tunnel tests are performed in the hole body.

The structure of a typical continuous transonic wind tunnel is shown below in Figure 2. It is a continuous transonic wind tunnel built in China at the end of 2012. It is a low-noise variable density flowback wind tunnel that uses dry air as an experimental medium. The design of this wind tunnel adopted many technical means to improve the quality of the wind tunnel flow field and to improve the operational efficiency of the wind tunnel.

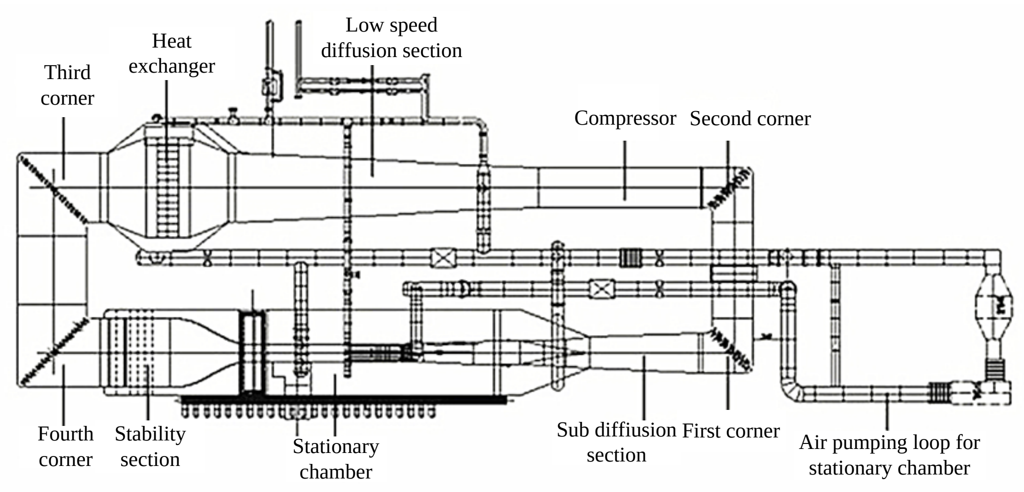

Figure 2. Structure of the wind tunnel system.

When the wind tunnel was ready for the experiment, all the main exhaust valves had to be closed, and when the main pressure regulating valve was started, the wind tunnel flow field started to form rapidly. After a period of time, the total air volume pressure in the stable section reached the target value. In order to better stabilize the flow field in the wind tunnel, the main exhaust valve started to operate, and the gas was emptied in time under the action of the controller, so that the total gas pressure in the stable section was stabilized near the target value. After a period of time, the static pressure of the test section also reached the target value. The Mach number then stabilized at the experimentally specified target value. Then, after the attitude of the aircraft model was changed according to the predetermined rules, the wind tunnel flow field was restored to the set conditions.

In wind tunnel systems, the working conditions are complex and varied. Generally speaking, the operating conditions are determined by the model, jet groove, opening/closing ratio, and total pressure control mode. Under the same working conditions, there are still many factors such as the attack angle step length, the speed setting value, and so on that affect the Mach number.

3.2. Models of the Multi-Mode Wind Tunnel Field

Using the data modeling method, all the system transfer functions at Mach numbers 0.4, 0.6, 0.8, 1.0, and 1.2, were obtained, respectively. The models are shown in Table 1.

Table 1. Models of the Multi-mode Wind Tunnel Field.

No.	Mach	Transfer Function
1	0.4	$G(s) = \frac{121}{s^2 + 29s + 62}$
2	0.6	$G(s) = \frac{101}{s^2 + 30s + 85}$
3	0.8	$G(s) = \frac{85.65}{s^2 + 30s + 120}$
4	1.0	$G(s) = \frac{113}{s^2 + 38s + 140}$
5	1.2	$G(s) = \frac{63}{s^2 + 46s + 150}$

As shown in Figure 3a–e, the response of the transfer function obtained using the data modeling method was relatively close to the actual data under the given step input at Mach numbers 0.4, 0.6, 0.8, 1.0, and 1.2. The sampling period was set at 0.05 s for a total of 20 s. Therefore, it can be considered that the transfer function obtained by the data modeling method could well reflect the operating characteristics of the wind tunnel system, and that the data modeling method of the multi-mode wind tunnel flow field modeling was effective and able to meet the additional accuracy requirements for Mach number control.

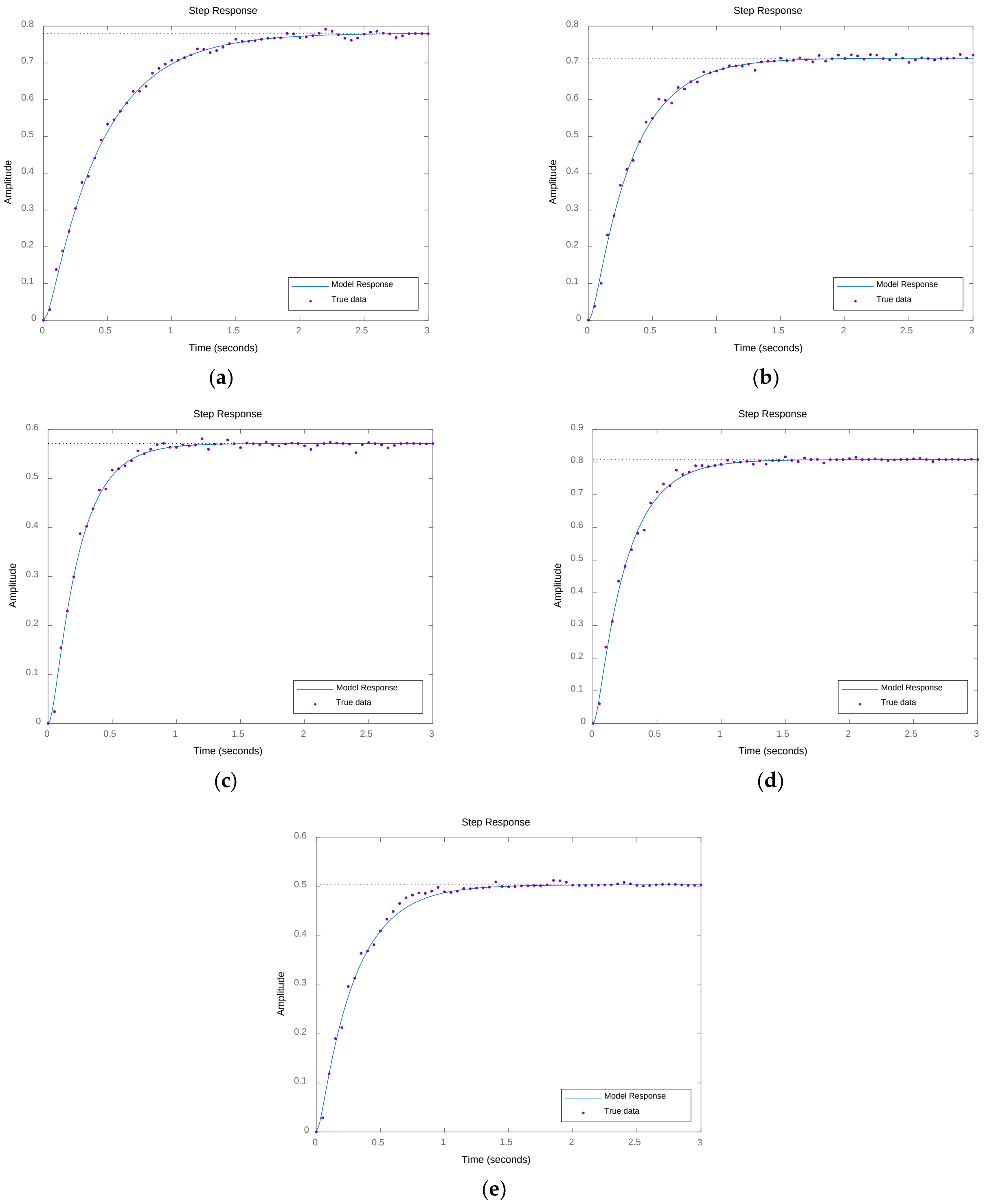

Figure 3. Model response under step input. (**a**) Mach 0.4. (**b**) Mach 0.6. (**c**) Mach 0.8. (**d**) Mach 1.0. (**e**) Mach 1.2.

3.3. Control of the Multi-Mode Wind Tunnel Field

For the multiple modes of the flow tunnel flow field at Mach 0.6, 0.8, and 1.0, PID control systems were established. A genetic algorithm was utilized to optimize the parameters

k_p, k_i, and k_d; to compare the results, the PSO algorithm was also used to obtain another set of parameters. Both of the control effects were compared and analyzed.

In detail, in the GA, the population was set to 30 and the number of termination evolution generations was set to 100. In the final error function, $w_1 = 0.999$, $w_2 = 0.001$, $w_3 = 2.0$, and $w_4 = 100$. The crossover probability was 0.6 and the variation probability was set to 0.01.

By applying the GA program, the resulting PID parameters were as shown in Table 2. Meanwhile, for comparison, the PSO algorithm was used to obtain another set of PID parameters. The parameters were input into the PID controller in Simulink to verify the effects by simulation, and the outputs of the two control systems were observed and displayed as in Figure 4 to facilitate direct observation and comparisons.

Table 2. PID parameters.

Mach	GA Tuning PID			PSO Tuning PID		
	k_p	k_i	k_d	k_p	k_i	k_d
0.6	39.9609	13.4311	0.6716	30.00	10.6316	0.5051
0.8	39.9609	12.5318	0.6266	35.00	5.000	0.4891
1.0	39.9609	11.3392	0.2464	20.00	12.6822	0.4891

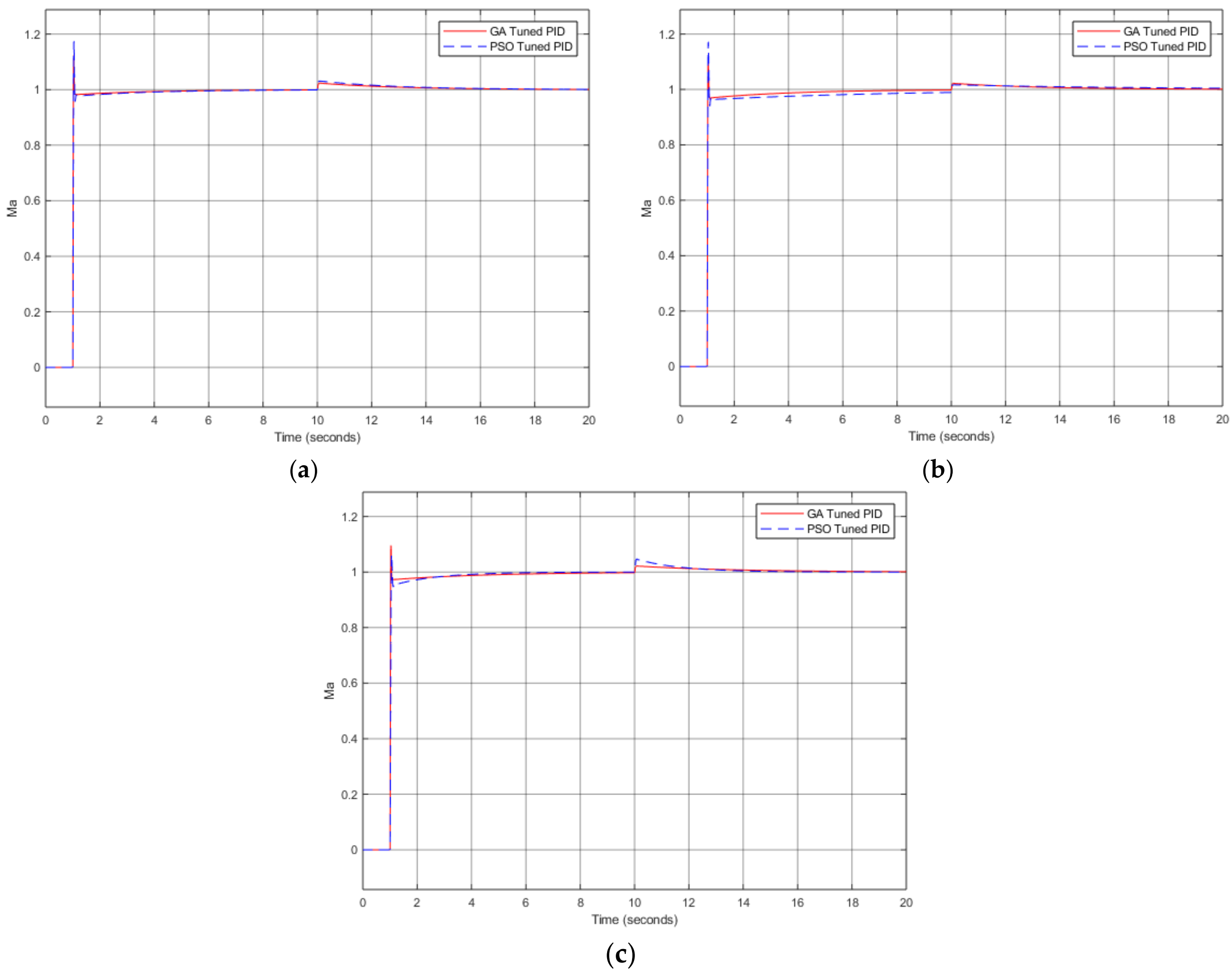

Figure 4. Mach number control results. (**a**) Mach 0.6. (**b**) Mach 0.8. (**c**) Mach 1.0.

The adjustment time (5% range) and the adjustment time after disturbance are listed in Table 3. It can be seen from the data that the adjustment times of the GA tuning PID controller were shorter than those of the PID controller set by the PSO algorithm. Thus, the control effect of the GA tuning PID controller was better than that of the PID controller set by the PSO algorithm.

Table 3. Control quality indexes.

Mach	GA Tuning PID		PSO Tuning PID	
	Adjustment Time(s)	Adjustment after Disturbance (s)	Adjustment Time(s)	Adjustment after Disturbance(s)
0.6	3.61	2.235	3.758	2.604
0.8	4.958	3.084	5.734	3.306
1.0	2.188	1.514	2.447	2.401

To intuitively represent the differences in the control effects of these two parameter tuning methods, the optimal error function results obtained by the two algorithms were compared, as shown in Figure 5 below. The stable optimal error function value obtained by the GA as well as the PSO algorithm are listed in Table 4. The smaller the error function, the higher the individual fitness. Therefore, the optimal individual obtained after the GA iteration was better than that in the PSO algorithm, and so the optimization effect of the GA was better.

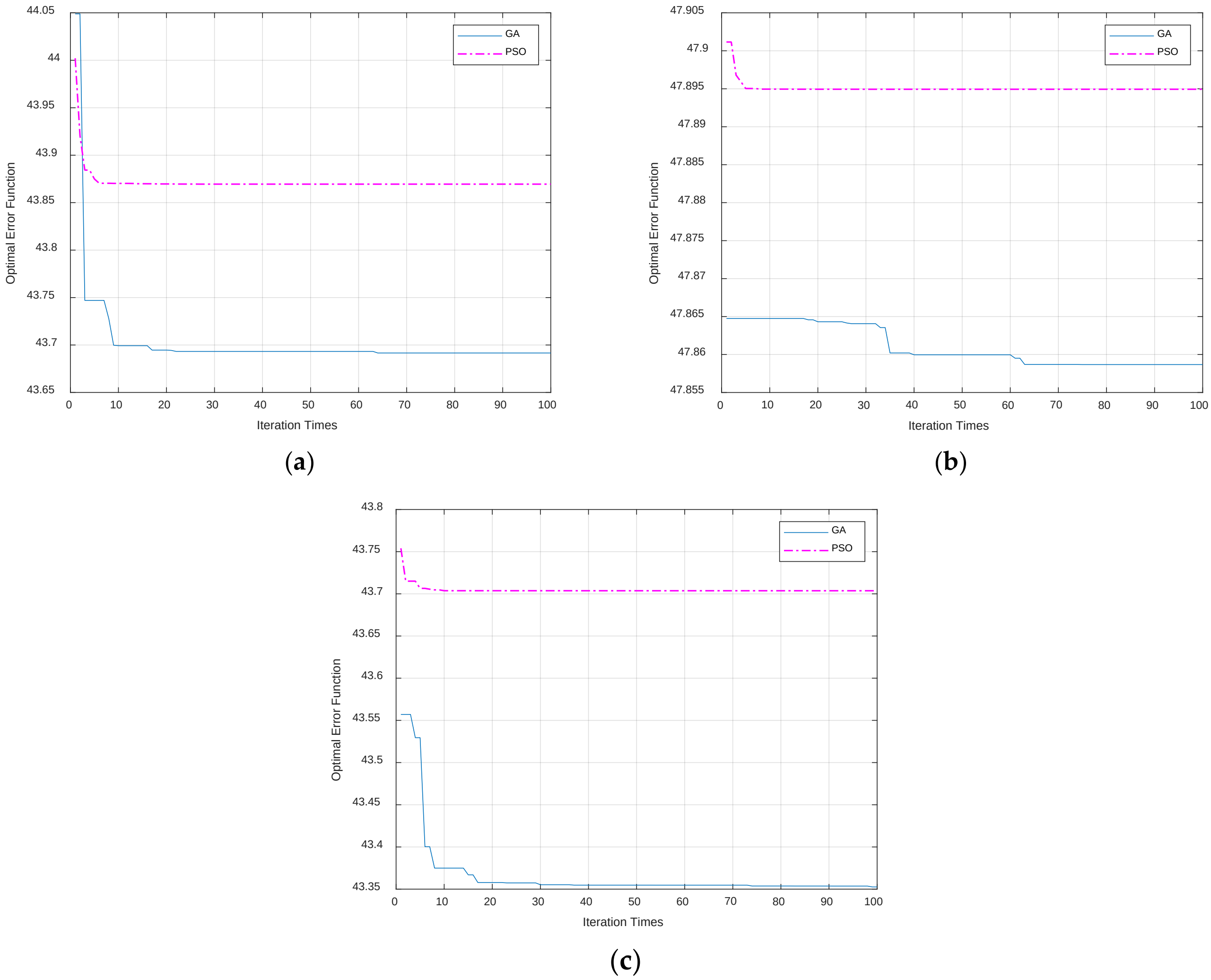

Figure 5. Optimal error function. (**a**) Mach 0.6. (**b**) Mach 0.8. (**c**) Mach 1.0.

Table 4. Optimal error function results.

Mach	GA Tuning PID	PSO Tuning PID
0.6	43.70	43.87
0.8	47.86	47.90
1.0	43.40	43.70

From the above analysis, for the multi-mode flow tunnel flow field, PID control systems with their parameters tuned by the GA had better control performances than those with their parameters tuned by PSO.

4. Conclusions

In this paper, the modeling and control of the Mach number of a multi-mode wind tunnel flow field was investigated and accomplished. In accordance with the problem of the models being different in the multiple modes of the wind tunnel, different working conditions were modeled, and the data modeling method was adopted to build the multi-mode wind tunnel flow field model. Later, a GA was used to adjust the PID parameters that were used for each established wind tunnel flow field model to achieve multi-mode Mach number control. The PID control system tuned by the GA was compared with that tuned by the PSO algorithm. The results showed the performance superiority of the control effect of the PID control system based on the GA in terms of the adjustment time and the adjustment time after disturbance.

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References

1. Ju, X.F.; Wang, X.L.; Gao, Y. Wind tunnel flow field model predictive control based on multi-model. *Control. Eng. China* **2018**, *25*, 1830–1835.
2. Yi, F.; Li, X.R.; Du, N.; Yu, W.S. Iterative learning based control for wind tunnel Mach number. *Control. Eng. China* **2020**, *27*, 109–113.
3. Jin, Z.W.; Ma, Y.Y.; Zhang, P.; Zeng, F.B. Research on Synchronization Control Strategy of Finger Choke Device in 2.4m Transonic Wind Tunnel. *Ordnance Ind. Autom.* **2014**, *33*, 46–48.
4. Yang, S.W. *Study of Generalized Predictive Control Method for Wind Tunnel Mach Number*; Northeastern University: Boston, MA, USA, 2016.
5. Ju, X.F. *Predictive Control for Wind Tunnel Flow Field Based on Multiple Models*; Northeastern University: Boston, MA, USA, 2016.
6. Gao, H.; Liu, X.J.; Guo, J.; Lv, H.Q. Mach number control of continuous wind tunnel based on Gaussian process regression. *ACTA Aerodyn. Sin.* **2019**, *37*, 480–487.
7. Lian, X.F. *Wind Tunnel Mach Number Control of BP Network based on Genetic Algorithm*; Northeastern University: Boston, MA, USA, 2011.
8. Nott, C.R.; Olcmen, S.M.; Williams, K. Supersonic, variable-throat, blow-down wind tunnel control using genetic algorithms, neural networks, and gain scheduled PID. *Appl. Intell.* **2008**, *29*, 79–89. [CrossRef]

9. Holland, J.H. *Adaptation in Natural and Artificial Systems*; University of Michigan Press: Ann Arbor, MI, USA, 1975.
10. Kennedy, J.; Gireesha Obayyanahatti, B. Particle swarm Optimization. In Proceedings of the ICNN'95-International Conference on Neural Networks, Perth, WA, Australia, 27 November–1 December 1995.