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RESEARCH ARTICLE

Optimization Technology of Combustion Engine Control Based on Swarm Intelligent Optimization Algorithm and Improved Clustering Algorithm

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ABSTRACT Since control instructions are the fundamental component of thermal power generation, the quality and effectiveness of implementation directly affect the efficiency of the energy system. In order to improve the efficiency of internal combustion engine control, an optimization method of internal combustion engine control based on enhanced clustering algorithm and swarm intelligence optimization algorithm is proposed. The process simplifies the main structure of the gas turbine, divides the combustion engine model into multi-input single-output systems, and introduces the artificial bee colony algorithm to optimize the parameters. A new nectar search formula is constructed by using the global optimal nectar, and the control parameters are calculated by fuzzy logic clustering. The experimental results showed that the modeling error of the load model of internal combustion engine was in the range of -0.47 MW $\sim$ 0.51 MW. When the training iteration speed was tested, the loss value of the research method dropped rapidly in the first 10 iterations. When analyzing the change of the control quantity during load change, if the exhaust flow rate was taken as the control quantity, the control results of the research method was always kept within 5lbm/s error. It demonstrates that this research method can effectively improve the running quality of the internal combustion engine and has a good running efficiency. The research can provide certain technical reference for gas turbine control in thermal power generation.

INDEX TERMS Combustion engine, control, swarm intelligence optimization algorithm, clustering algorithm, fuzzy logic, fireworks algorithm.

I. INTRODUCTION

Rapid economic expansion has raised social demand for energy in the context of globalization, which not only helps the energy industry flourish but also presents a significant threat to the sustainable use of energy. Thermal power generation, as an important part of the global power supply, consists of the core equipment, the combustion turbine, for efficient and stable power output [1]. The operating efficiency of the combustion turbine directly affects the energy efficiency and environmental performance of the entire power generation process. Due to the inherent complexity of the gas turbine (GT) system, it makes the traditional control methods incompetent in dealing with non-linear, multi-variable coupling problems [2]. Some scholars have conducted relevant research on the control of GTs. Reggio F et al. proposed a method using real-time diagnosis to address the issue of GT control. The study designed shock prevention tools based on control criteria, optimized procedures for different equipment types, and designed self-programming software to enhance flexibility. The experimental results showed that the proposed method could improve the control parameters of the GT [3]. Ramoji et al. proposed a technology based on voltage frequency unified control to address the load frequency control problem in GT control. During the process, a tilted integral differential controller with a filter was used to control the air state, and a meta heuristic algorithm was combined to provide controller gain. The experimental results indicated

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that the proposed method had high control sensitivity [4]. Bhuyan et al. proposed a method based on chaotic butterfly optimization algorithm for frequency control in GT control. In this process, the study obtained optimization criteria for dispatchable generating units and integrated the hybrid micro-grid system as a whole, and the results indicated that the proposed method had high control accuracy [5]. Stefan proposed a technology based on material development for the control of GTs. This study analyzed the diffusion mechanism of thermal corrosion and the double atmosphere effect in the matrix alloy during the process. The experimental results indicated that the proposed method could effectively improve the operational efficiency of the GT [6]. Serbin proposed a method based on combustion chamber characteristics research to address the issue of combustion engine control. This study analyzed the combustion process of the mixture in the process, modeled the combustion, and set the conditions and operating modes for not forming a reverse combustion zone. The results indicated that the proposed method could effectively improve the operational quality of GTs [7].

To further improve the control efficiency and quality of GTs, researchers are also constantly exploring more advanced control theories and technologies. The swarm intelligence optimization algorithm has demonstrated excellent performance in global search and local optimization [8]. Some scholars have conducted relevant research on swarm intelligence optimization algorithms. Su S proposed a technology based on swarm intelligence optimization algorithm for the optimization of asymmetric eccentric load steel box girder structures. During the process, weight reduction was taken as the calculation objective, and multiple constraint conditions were established to optimize the cross-sectional parameters. Grey wolf optimization algorithm was introduced for optimization. The experimental results showed that the technology based on swarm intelligence optimization algorithm had good computational performance [9]. Li proposed a technology based on swarm intelligence optimization algorithm to address the issue of mine safety blasting design. During the process, fruit fly optimization and sparrow search were used to process input parameters, combined with root mean square error and variance ratio to improve performance. The experimental results showed that the swarm intelligence optimization algorithm had achieved high accuracy in security prediction [10]. Kivi proposed a method based on swarm intelligence optimization algorithm for solving complex problems. During the process, the movement of the flock served as an inspiration, and the guidance of the shepherd and the proximity of interests between the sheep combined to set iterative conditions. The ranch was the problem domain. The experimental results indicated that the proposed method has good computational speed [11]. Saeed proposed a technology based on swarm intelligence optimization algorithm for the problem of unmanned aerial vehicle path planning. During the process, comprehensive consideration was given to obstacle avoidance and avoidance speed, searching for the shortest path between the starting point and the target point, and optimizing the obstacle avoidance route based on the position of obstacles. The experimental results indicated that the proposed method had fast planning efficiency [12]. Chang et al. proposed a technique based on a body intelligent optimization algorithm for the problem of channel optimization. The process performed hierarchical channel clustering by similarity of feature mapping and generated candidate populations for iteration to compress the network structure. According to experimental results, the suggested strategy achieved a high level of optimization accuracy [13]. The comparison between research methods and existing advanced algorithms is shown in Table 1.

SIOA has been shown to be able to solve complex optimization problems, providing a technical basis for application to optimization solving for combustion engine control. Clustering algorithm (CA), as an unsupervised learning method in data mining, helps to reveal the intrinsic structural features of the data by dividing the samples in the dataset into clusters based on similarity [14], [15], [16]. In the control optimization of GT, CA can be used to analyze and identify different modes in system operation and provide data support for control strategy development. However, the existing SIOA or CA still has many challenges in practical applications. For example, issues such as the algorithm's parameter selection, search efficiency, and sensitivity to initial conditions affect the algorithm's performance in control optimization problems [17], [18]. In light of the aforementioned context, the study endeavors to innovatively combine the artificial bee colony (ABC) and fireworks algorithm (FA) in SIOA and utilize clustering through fuzzy logic (FL) as a means of clustering, thereby proposing a novel technique for solving the control parameters of combustion turbines and achieving combustion turbine real-time control of the combustion engine. This is done with the objective of providing certain technical references for the thermal power generation and automation control industry. The contributions of the research method are as follows: (1) The combustion engine model is transformed into a multi-input multi-output system. The global output of the model is calculated using the local non-linear weighting method, which enhances the adaptability of the model to practical engineering problems and the prediction accuracy. (2) The introduction of FL clustering serves to enhance the adaptability of data distribution. When combined with covariance matrix calculation, the over-fitting problem is effectively avoided, thereby enhancing the robustness of the control strategy.

There are three parts in the research. In the first part, combustion engine control technology (CECT) based on SIOA and improved clustering algorithm (ICA) is designed, and the main technical components and implementation ideas are described. The application analysis and performance testing of CECT based on SIOA and ICA are the main topics of the second section. The last part is a discussion and summary of the whole study.

TABLE 1. Comparison of existing advanced methods.

Method	Main technical features	Advantage	Inferior position	Reference
Operation extension	Associative control standard	Enhanced combustion engine control parameters	High real-time requirements and high hardware requirements	Reggio F et al [3]
Optimal coordinated frequency	Using a tilted integral differential controller	High control sensitivity	Parameters need to be adjusted frequently	Ramoji S K et al [4]
Chaotic butterfly optimization	Optimized for frequency control	Demonstrated high control accuracy	Enough iterations are needed to stabilize	Bhuyan M et al [5]
Hydrogen-fuelled	Thermal corrosion and dual atmosphere effects are analyzed	It improves the efficiency of the combustion engine	An in-depth understanding of new material properties is required	Stefan E et al [6]
Combustion chamber operating	Combustion modeling	The operation quality of combustion engine is improved	The model establishment is more complicated	Serbin S et al [7]
Structural optimization	Swarm intelligence optimization algorithm	It is suitable for solving the problem of asymmetric eccentric loading	Specific types of optimization problems are required for maximum effect	Su S et al [9]
Extreme learning machine–swarm intelligence optimization	Optimize processing input parameters	It provides good safety prediction accuracy	It needs to be adjusted for specific problems	Li C et al [10]
Grazing of sheep	Inspired by herd behavior	Fast computing speed	Adjustments need to be made for problem specificity	Kivi M E et al [11]
Swarm intelligence algorithm	Consider obstacle avoidance	Provides faster planning efficiency	The accuracy of path planning in complex environment needs to be verified	Saeed R A et al [12]
clustering and swarm intelligence	Hierarchical channel clustering	High optimization accuracy	It requires a lot of data support	Chang J et al [13]
This study	Combining artificial bee colony algorithm and fireworks algorithm	The control precision and real-time performance are improved	More computing resources may be required	This study

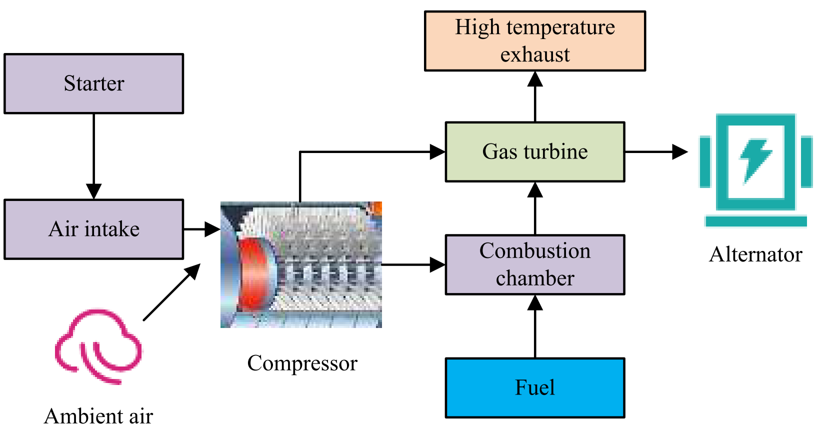

FIGURE 1. Main structure of gas turbine.

II. DESIGN OF COMBUSTION ENGINE CONTROL TECHNOLOGY BASED ON SIOA AND ICA

A. COMBINED COUPLING RELATIONSHIP FOR COMBUSTION ENGINE MODELING

Thermal power generation, as the most common and stable source of electric energy, is used in a large number of applications around the world. However, the combustion engine, which is the core of thermal power generation, has the problems of non-linearity as well as being susceptible to external perturbations, and ordinary control strategies cannot realize stable and accurate control [19], [20], [21]. To design the more advanced CECT, the study simplifies the main structure of GT, as shown in Figure 1.

In Figure 1, during the operation of the GT, ambient air is first introduced into the pressurizer through the air inlet. The air is compressed by the axial flow compressor, which produces a pressurization effect of several tens of times. During the compression process, the temperature of the air

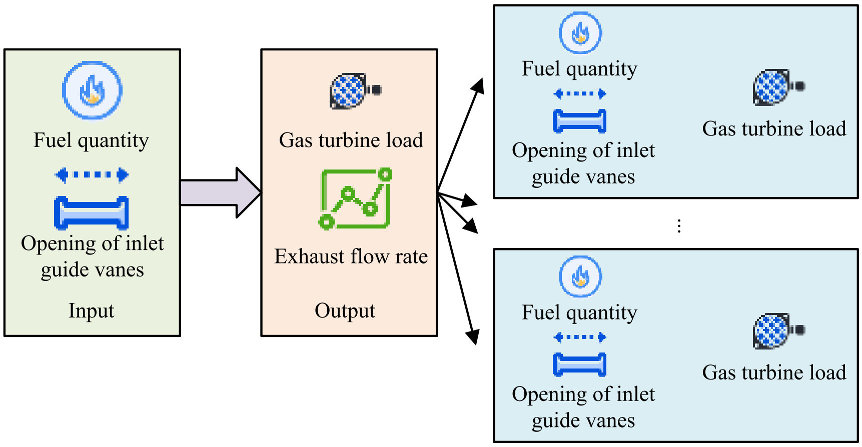

FIGURE 2. Input/output system structure.

rises accordingly. The compressed air enters the combustion chamber where it is mixed with the fuel and burned to produce a high-temperature, high-pressure gas mixture. The generated high-temperature and high-pressure gas is fed into the GT to drive the turbine to rotate, which in turn drives the rotor of the external load to rotate rapidly [22], [23]. The conversion of chemical energy to mechanical and electrical energy is realized by expansion work during the process. In the control process of GT, achieving high power generation efficiency and ideal exhaust flow (EF) are the main control objectives of the system [24], [25]. The fuel supply must be adjusted to the load's fluctuating demand in order to maintain the plant's efficient operation. By adjusting the opening of inlet guide vanes (OIGV) of the GT, the amount of air entering the pressurizer is varied, which in turn maintains the proper ratio of fuel to air and sustains the combustion efficiency. In Figure 2, the study defines the input-output system's structure.

In Figure 2, the study transforms the combustion engine model into a multi-input multi-output system and divides it into several multi-input single-output systems. OIGV and fuel quantity are taken as system inputs. EF and combustion engine load are taken as system outputs. The multi-input single-output system is constructed from two system inputs and one of the system outputs, respectively. The input vector (IV) is shown in Equation (1).

$$\begin{aligned}\vartheta(k) = \big[&u_1(k), \ldots, u_1(k-q_1), \ldots, u_p(k), \\ &\ldots, u_p(k-q_p), y(k), \ldots, y(k-\tau)\big]^T\end{aligned} \tag{1}$$

In Equation (1), $\vartheta(k)$ is the IV and u is the manipulated variables. k represents the time series and q represents the order of the different manipulated variables. τ represents the order of the output variables. The data of OIGV and fuel quantity as well as the steady state values of combustion engine power are imported and equivalently regarded as clustering centers to compute the non-linear outputs as shown in Equation (2).

$$yn_i(k) = yv_i(k) + yss_i \tag{2}$$

In Equation (2), $yn_i(k)$ represents the non-linear output of rule i. $yv_i(k)$ represents the incremental data input and yss_i represents the steady state value of combustion engine power. The local non-linear weighting calculation is performed to obtain the global output of the model, as shown in Equation (3).

$$y(k) = \frac{\sum_{i=1}^{n} w_i \cdot yn_i(k)}{\sum_{i=1}^{n} w_i} \tag{3}$$

In Equation (3), $y(k)$ is the global output and w_i is the affiliation function.

B. SIOA-BASED OPTIMIZATION ALGORITHM FOR COMBUSTION ENGINE CONTROL PARAMETERS

When performing optimization of combustion engine control parameters, the study uses an adaptive approach to select the clustering center closest to IV. ABC, as a SIOA with few parameters and strong exploration capability, has good performance on data search tasks [26], [27]. Compared with other meta-heuristic algorithms, the ABC algorithm requires fewer parameters to be adjusted, including only a few key parameters such as population size, maximum number of cycles, and maximum number of failures. There is no need to adjust the learning factors, mutation rates, and crossover rates that other algorithms need to adjust, reducing the workload of parameter adjustment and making the algorithm easier to implement and apply. The ABC algorithm is designed to identify the optimal solution, with the intelligent selection of parameters achieved through the simulation of social behavior observed in bees. Principal component analysis is a statistical method employed for the reduction of dimensionality in data sets, with the objective of extracting the principal features of the data. In addition, principal component analysis and dimensionality reduction are mainly used for pre-processing basic data, and can play little role in optimizing GT control parameters. The study introduces ABC for

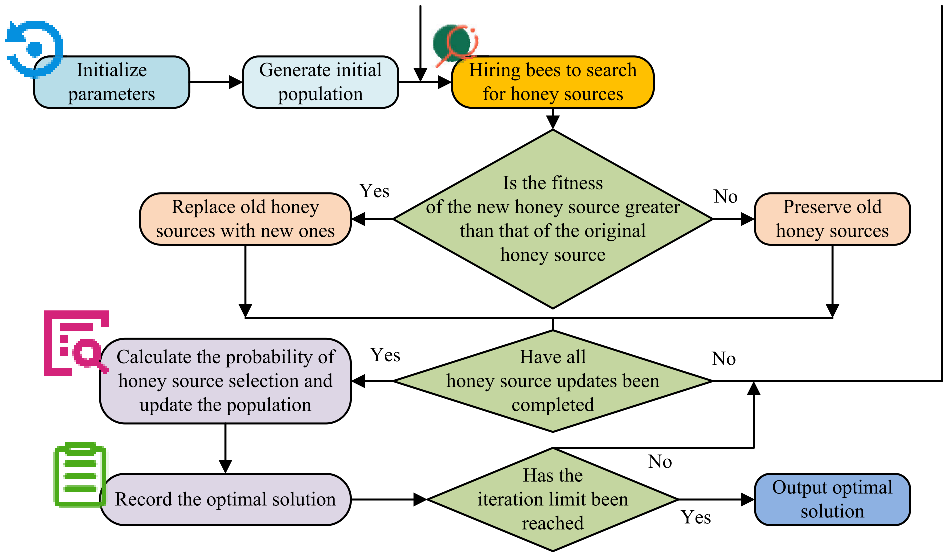

FIGURE 3. The process of solving artificial bee colony algorithm.

parameter optimization to determine the combustion engine model's premise parameters. The ABC solving process is shown in Figure 3.

In Figure 3, ABC can be divided into a total of five running phases when performing the solution: initialization, hiring bee operation, observing bee operation, recording the optimal solution, and detecting bee operation. When initialization is performed, the dimension, population size, maximum retry limit, and maximum number of cycles need to be set. Then the honey source is randomly generated as shown in Equation (4).

$$x_{ij} - x_{j\min} + rand\left(x_{j\max} - x_{j\min}\right)\ (i = 1, \ldots, SN; \quad j = 1, \ldots, D) \tag{4}$$

In Equation (4), x_{ij} represents the nectar source as the center of clustering, and x_{ic} is the limit value of the jth dimension solution. $rand\ (\cdot)$ is randomized calculation, SN is the bee colonies, and D is the data dimension. The evolutionary direction of the bee colony population is guided by the fitness function, and the study uses the clustering accuracy as the fitness function. When the distance within the cluster is small, it means that the data points within the cluster are less different from each other, which indicates that it is reasonable to group these data points into one cluster [28], [29], [30]. Equation (5) illustrates the construction of the fitness function.

$$fit\ (X_i) = \frac{C_i}{J_i} \tag{5}$$

In Equation (5), $fit\ (\cdot)$ represents colony fitness and C_i is the elements in the ith class. X is the honey source, and J_i is the distance between the data in the i th class and the cluster center point. Employed bees perform the honey source search, and in order to increase the convergence efficiency of the search. The study constructs a new formula for the honey source search by introducing the global optimal honey source as shown in equation (6).

$$z_{ij} = x_{ij} + \gamma_{ij}\left(x_{ij} - x_{kj}\right) + rand\left(x_{gj} - x_{ij}\right) \tag{6}$$

In Equation (6), z_{ij} represents the new nectar source location and γ_{ij} represents a uniformly distributed random number between -1 and 1. x_{gj} is the value of the global optimal nectar source in dimension j. The adaptation values are compared based on greedy search to remove the honey sources with lower adaptation. Roulette is performed by combining the information obtained by the hired bees, as shown in Equation (7).

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{7}$$

In Equation (7), P_i represents the nectar source selection probability. The in-depth search is performed in the vicinity of high-adaptation nectar sources. However, ABC has insufficient convergence speed in the whole. There are some defects in the late exploration ability, and the study introduces FA to optimize the late computation stage of ABC. If the nectar source is in the limit number of iterations, the fitness value remains unchanged, then enter the fireworks explosion search stage. Figure 4 depicts the firework explosion algorithm's flow.

In Figure 4, the firework explosion algorithm needs to randomly generate a certain number of fireworks first during operation, search the neighborhood near the fireworks by the exploding sparks, and enrich the diversity of the solution space by Gaussian activation. The quality of the sparks is represented by the fitness value, and the minimum fitness value is used as the condition for progress determination. Moreover, the iteration is stopped when the required accuracy

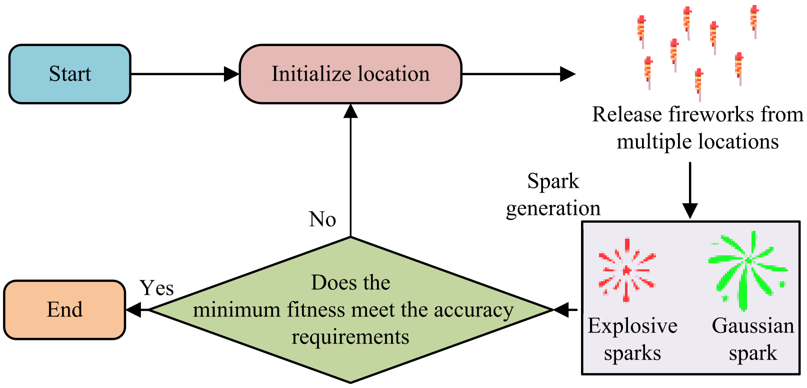

FIGURE 4. Fireworks explosion algorithm flow.

is reached [31], [32]. In the context of combustion engine control parameter optimization within the ABC framework, three nectar sources are selected for the purpose of conducting a fireworks explosion search. Once the optimal individual has been identified, the remaining individuals are selected based on their distance from the optimal individual. Equation (8) is used to compute the nectar source distances.

$$S(X_i) = \sum \left\| X_i - X_j \right\| \tag{8}$$

In Equation (8), $S(X_i)$ represents the distance between the nectar sources. The remaining nectar sources are chosen according on probability, and when the fireworks go off, sparks keep forming around them to create new ones. Equation (9) shows how many sparks are produced by the sparks.

$$B_i = B\frac{fit_{\max} - fit(X_i) + \xi}{\sum_{i=1}^{ES}(fit_{\max} - fit(X_i)) + \xi} \tag{9}$$

In Equation (9), B_i is the ith individual. B is the initialized number and ξ is a very small constant term. The spark amplitude is obtained and then the position is shifted to produce a new explosive spark as shown in Equation (10).

$$X_i^{t+1} = X_i^t + randA_i \tag{10}$$

In Equation (10), X_i^{t+1} represents the new explosive spark and X_i^t represents the original explosive spark. A_i represents the radius of the ith individual.

C. COMBUSTION ENGINE CONTROL TECHNOLOGY DESIGN IN CONJUNCTION WITH ICA

When performing combustion engine control parameter optimization, ordinary clustering means are more sensitive to the initial clustering center. FL-based clustering allows flexibility in the shape and direction of clusters by introducing an adaptive distance metric, which better adapts to the actual distribution of data [33], [34]. The study uses FL's clustering as a means of clustering and introduces SIOA into FL's clustering for initial cluster center calculation. The initial clustering center calculation process is shown in Figure 5.

In Figure 5, when using SIOA to calculate the initial cluster centers, the parameters are initialized first, and then the nectar sources are initialized. The clustering compactness is obtained after calculating the fitness function, and the global optimization individual is introduced to generate new nectar sources and select the best solution. When the number of times the nectar source is not updated is greater than or equal to the maximum retry limit, the explosion search phase is entered. The radius and number of firework explosions are computed to generate new positions and sorted to obtain the best solution. The calculation ends when the total number of cycles reaches the upper limit of predicted cycles, and the initial clustering center is output. For CA solving, the study introduces covariance matrix calculation to avoid over-fitting conditions. The covariance matrix calculation is performed using OIGV, fuel quantity, and combustion engine load steady state as IV as shown in Equation (11).

$$F_i = \frac{\sum_{k=1}^{NN}\left(\mu_{ik}^{(l-1)}\right)^m \left(zz_k - X_i^l\right)\left(zz_k - X_i^l\right)^T}{\sum_{k=1}^{NN}\left(\mu_{ik}^{(l-1)}\right)^m} \tag{11}$$

In Equation (11), F_i represents the covariance matrix and m represents the fuzzy index. μ represents the affiliation matrix, l is the current iterations, and zz is the data set. A scaling matrix is added to the matrix as shown in Equation (12).

$$F_{mew} = (1-\kappa)\,F_i + \kappa \det(F_0)^{\frac{1}{n}} I \tag{12}$$

In Equation (12), F_{mew} represents the scaling matrix and κ represents the scaling factor. F_0 represents the full dataset covariance matrix. I represents the shape constraints. In clustering analysis, the clustering metric for each dataset is defined by the local paradigm induction matrix, which serves as a key variable in the optimization process and serves to adjust the distance metric to match the local structure of the data. After completing the chunking matrix update, all clustering centers are computed and obtained iteratively. After obtaining the clustering centers, the initial value of

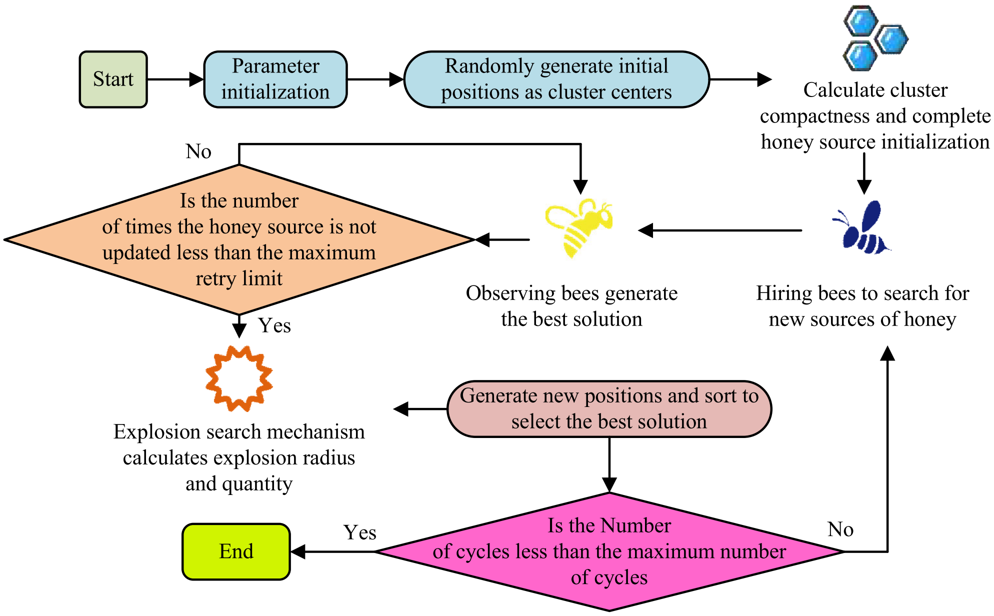

FIGURE 5. Initial clustering center calculation process.

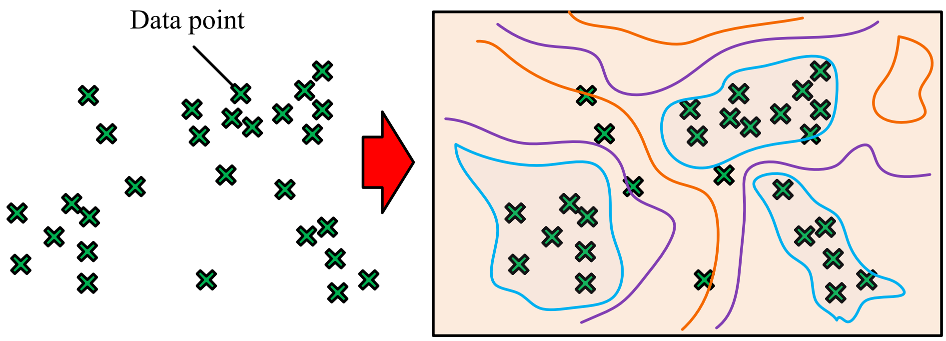

FIGURE 6. Clustering based on fuzzy logic.

the clustering radius is set to 0. The IV is imported to search for other clustering centers nearest to the current clustering center, and the clustering radius is continuously searched and updated. The FL-based clustering is shown in Figure 6.

In Figure 6, FL-based clustering divides regions by the distribution clusters of data points when clustering. The clustering region and type are decided based on the distribution density of data points. Some of the points that stray from the main data points are appropriately ignored to ensure the overall clustering effect. The combustion engine control parameter identification can generate the relationship between IV increment and linear output, and process the obtained combustion engine operation data into more linear incremental data. When the calculated control parameters of the combustion engine are input into the controller to realize the control of the combustion engine, model conversion is needed first. The sub-models obtained in modeling are fuzzy weighted to obtain the total model with adaptive capability, and then the total model is used as the object of global non-linear control, as shown in Equation (13).

$$yv = \frac{\sum_{i=1}^{n} w_i y v_i}{\sum_{i=1}^{n} w_i} \tag{13}$$

A most suitable adaptive model is converted in each sampling cycle and the adaptive model is shown in Equation (14).

$$A\left(z^{-1}\right) y\left(t\right) = B\left(z^{-1}\right) u\left(t\right) + \frac{C\left(z^{-1}\right) e\left(t\right)}{\Delta} \tag{14}$$

In Equation (14), $y(t)$ is the control system output and $u(t)$ is the control system input. $e(t)$ is white noise and Δ is the difference factor. $A\left(z^{-1}\right)$ is the matrix whose side lengths are the output quantities, and $B\left(z^{-1}\right)$ is the matrix whose quantities side lengths are the input and output quantities, respectively. Diophantine equations are introduced to predict the future behavior and the obtained control quantities are

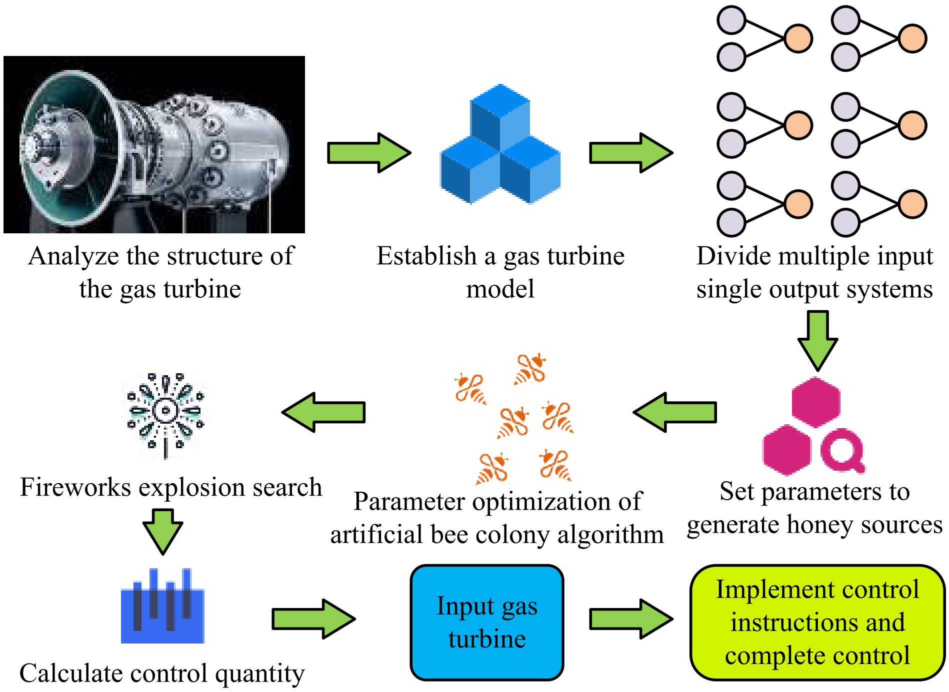

FIGURE 7. Gas turbine control optimization technology operation flow.

used to control the object only in the first step and then new control quantities are obtained every cycle. The idea of step control is used to display and plan the future control increments, generate the optimal control rate, and perform the control by implementing only the present control quantity (CQ). Equation (15) is used to calculate the current CQ.

$$u(t) = u(t-1) + \delta \tag{15}$$

In Equation (15), $u(t)$ is the current CQ, $u(t-1)$ is the previous moment CQ, and δ represents the optimal control rate. The operation flow of the research-designed combustion engine control optimization technology is shown in Figure 7.

In Figure 7, the research method needs to study the main structure of GT first when performing combustion engine control and transform the combustion engine model into a multi-input multi-output system, which is divided into several multi-input single-output systems. The initial step is to set the dimensions, population size, maximum retry limit, and maximum cycle number. Subsequently, the nectar source should be randomly generated, and the combustion engine control parameter optimization should be conducted using the ABC method. When the nectar source adaptation value remains constant in the limit number of iterations, the firework explosion search phase is entered. The clustering of FL is used as a means of clustering, and an adaptive distance metric is introduced to adapt to the actual distribution of the data. A most suitable adaptive model is transformed in each sampling cycle, and the step control idea is used to calculate the CQ of the moment and implement the control of the combustion engine. The ABC algorithm is designed to identify the optimal solution, with the intelligent selection of parameters achieved through the simulation of social behavior observed in bees. Principal component analysis is a statistical method employed for the reduction of dimensionality in data sets, with the objective of extracting the principal features of the data. In addition, principal component analysis and dimensionality reduction are mainly used for pre-processing basic data and can play little role in optimizing GT control parameters. Therefore, the study added an anomaly detection mechanism in the stage after data addition to identify and analyze newly added data points in ABC and remove outliers from them. Promote ABC to achieve better results in solving GT control parameters. In order to balance the computational efficiency and clustering quality of ABC and principal component analysis methods during runtime, batch sizes are adjusted based on real-time monitoring of system load and data characteristics to achieve optimal allocation of computing resources.

III. EFFECTIVENESS ANALYSIS OF COMBUSTION ENGINE CONTROL TECHNOLOGY BASED ON SIOA AND ICA

A. PERFORMANCE TESTING OF COMBUSTION ENGINE CONTROL TECHNOLOGY BASED ON SIOA AND ICA

To analyze the performance of the research-designed CECT during operation, the study uses the combustion turbine control system fault dataset and the GT control logic data of Huadian Electric Power Research Institute (HEPRI) as the test data. Table 2 displays the fundamental hardware environment configuration for the investigation.

In conducting the tests, the research method, referred to as group intelligence-clustering (GI-C), is compared with

TABLE 2. The experimental basic environmental parameters.

Parameter variables	Parameter selection
Central processing unit	Intel i5-13400
CPU dominant frequency	2.62Hz
System PC side memory	12G
operating system	Windows10
GPU	RTX-3080
Operating environment	MATLAB2018b

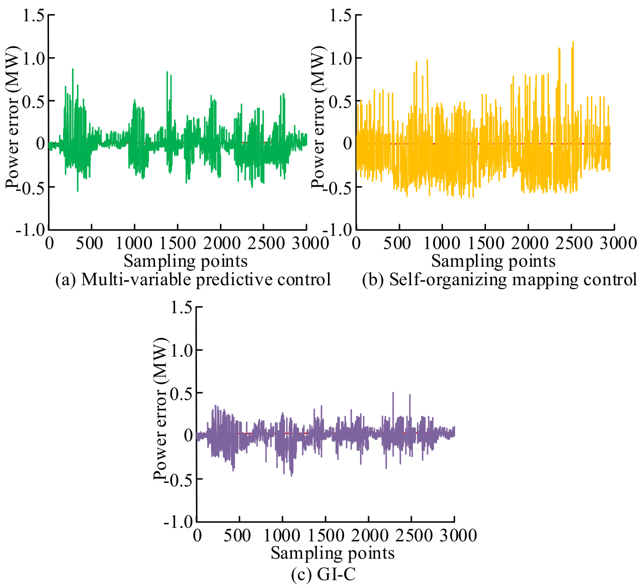

FIGURE 8. Gas turbine load model modeling error.

self-organizing mapping control and multi-variable predictive control techniques. Tests are performed on the modeling errors (MEs) of the combustion engine load model as shown in Figure 8.

In Figure 8, the MEs of the combustion turbine load models of the different methods are in different intervals. Figure 8(a) shows that the load model ME of the multi-variable predictive control technique is in the range of −0.55 MW to 0.82 MW for the 3000 sampling points, of which about 7% of the sampling points have a ME of more than 0.5 MW and about 50% of the sampling points have a ME of more than 0.3 MW. In Figure 8(b), the ME of the load model for the self-organizing mapping control is in the range of −0.61 MW to 1.23 MW, in which about 10% of the sampling points have a ME of 0.5 MW or more, and about 50% of the sampling points have a ME of 0.45 MW or more. In Figure 8(c), the load ME of GI-C is in the range of −0.47 MW to 0.51 MW, in which about 0.1% of the sampling points have a ME of 0.5 MW or more, and about 50% of the sampling points have a ME of 0.25 MW or more. It suggests that the combustion turbine load model can be more accurately modeled using the research approach. The ME of the combustion turbine EF model is tested as shown in Figure 9.

In Figure 9, the MEs of the combustion engine EF models of different methods are in different intervals.

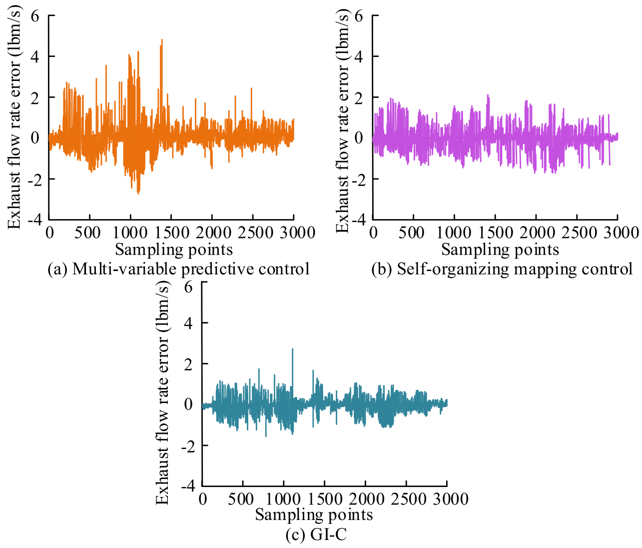

FIGURE 9. Modeling error of gas turbine exhaust flow model.

In Figure 9(a), the ME of the combustion engine EF model of the multi-variable predictive control technique is in the range of −2.8lbm/s to 4.8lbm/s among 3000 sampling points, of which about 8% of the sampling points have a ME of 2.0lbm/s or more, and about 50% of the sampling points have a ME of 1.2lbm/s or more. In Figure 9(b), the ME of the combustion engine EF model for the self-organizing mapping control technique is in the interval of −2.0lbm/s to 2.2lbm/s, in which about 1% of the sampling points have a ME of 2.0lbm/s or more, and about 50% of the sampling points have a ME of 1.4lbm/s or more. In Figure 9(c), the ME of the combustion engine EF model of GI-C is in the interval of −1.7lbm/s to 2.9lbm/s, in which less than 0.1% of the sampling points have a ME of 2.0lbm/s or more, and about 50% of the sampling points have a ME of 1.0lbm/s or more. It indicates that the research methods have higher modeling accuracy of the combustion engine EF model. The training iteration speeds of the different methods are tested, as shown in Figure 10.

In Figure 10, the training iteration efficiency of different methods has some differences. Figure 10(a) shows that when training in the fault data set of the combustion engine control system, the loss value of the multi-variable predictive control technique decreases rapidly in the first 5 iterations, and the loss value decreases to 0.057 when the iterations is up to 50 times. The loss value of the self-organizing mapping control technique decreases rapidly in the first 13 iterations, and the loss value decreases to 0.039 when the iterations is up to 50 times. the loss value of the GI- C loss value decreases rapidly in the first 10 iterations, and the loss value decreases to 0.023 when the number of iterations reaches 50. In Figure 10(b), the loss value of the multi-variable predictive control technique decreases rapidly in the first 5 iterations and the loss value decreases to 0.015 when the iterations is up to 50 when the training is performed in the GT control

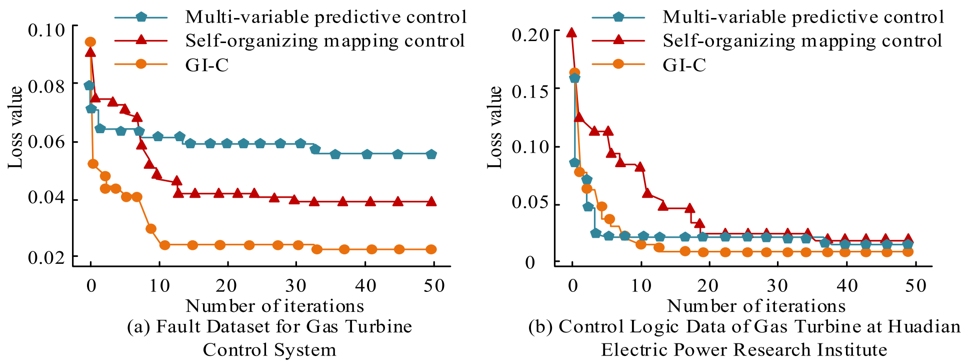

FIGURE 10. **Training iteration speed test.**

logic data of the WECC. The loss value of the self-organizing mapping control technique loss value decreases rapidly in the first 20 iterations and decreases to 0.021 when the iterations is up to 50. The loss value of GI-C decreases rapidly in the first 10 iterations and decreases to 0.007 when the iterations is up to 50.This indicates that the research method has better training results.

B. APPLICATION ANALYSIS OF COMBUSTION ENGINE CONTROL TECHNOLOGY BASED ON SIOA AND ICA

To determine the feasibility and application effectiveness of the research-designed CECT in carrying out the practical application, the study selected two combustion engines for the practical application analysis, called Alpha and Bravo, respectively. The computation time of the control parameters is analyzed as shown in Figure 11.

In Figure 11, the computation time of control parameters for different methods all rise with the increase in the number of input data bars. Figure 11(a) shows that in the Alpha combustion engine, the computation time of the multi-variable predictive control technique is 343ms for 1000 input data bars. The computation time of the multi-variable predictive control technique is 1891ms for 6000 input data bars. The computation time of the self-organizing mapping control technique is 477ms for 1000 input data bars. The computation time of the multi-variable predictive control technique is 2038ms for 6000 input data bars. The computation time for GI-C is 88ms for 1000 input data entries. The computation time for 6000 input data entries is 902ms. In Figure 11(b), the computation time of the multi-variable predictive control technique in the Bravo combustion turbine is 427ms for 1000 input data entries, and 2416ms for 6000 input data entries. The computation time of the self-organizing mapping control technique is 598ms for 1000 input data entries, and 1864ms for 6000 input data entries. The computation time for GI-C is 212ms for 1000 input data entries and 1121ms for 6000 input data entries. This indicates that the computational speed of the research approach is faster. The parameter optimization strategy introduced into the algorithm reduces invalid searches, speeds up convergence, and improves the ability of the algorithm to solve the problem through intelligent selection and adjustment of control parameters. In this study, the complex combustion engine model is decomposed into multi-input single-output systems, which simplifies the model structure, reduces the complexity of model calculation, and improves the operation efficiency. The change curve of the controlled quantity when the load changes is analyzed, as shown in Figure 12.

Figure 12 shows how the controlled quantity varies from the set value when various control strategies are applied during a load shift. As demonstrated in Figure 12(a), when the combustion engine's power is used as the controlled quantity, the power of the engine, under multi-variable predictive control technology, in the first 400 s can deviate from the set value by up to 20 MW, with the main trend of the change essentially being the same. The control results of the self-organizing mapping control technology show a maximum deviation of 10MW from the set value in the first 200s, and the power decreases and increases in the 300s to 400s. The overall trend of the control results by GI-C is consistent with the set value, and the error is kept within 1MW throughout the whole process. In Figure 12(b), when EF is used as the controlled quantity, the EF controlled by the multi-variable predictive control technique shows a maximum deviation of 20lbm/s from the set value in the first 200s, and the main trend of change is consistent with the set value. The control results of the self-organizing mapping control technique show abnormal rise and fall in the intervals from 0s to 100s and from 200s to 400s, and the maximum deviation reaches 30lbm/s or more. The overall trend of the control results by GI-C is consistent with the set value, and the error is kept within 5lbm/s throughout the whole process. It demonstrates that the accuracy of the load change combustion engine control is improved by the research approach. The change of the controlled quantity when the OIGV suffers a disturbance is analyzed, as shown in Figure 13.

In Figure 13, the control strategies generated by different methods have certain differences in their ability to eliminate external disturbances. Figure 13(a) shows that, when the combustion engine power is the controlled quantity, the control result of the multi-variable predictive control technique

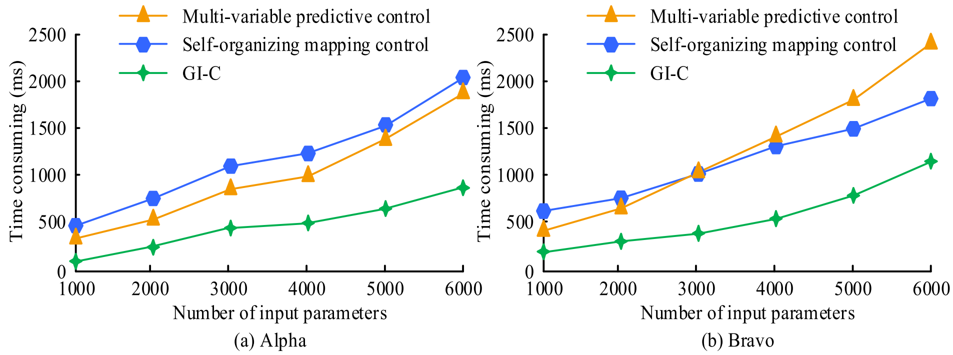

FIGURE 11. Control the calculation time of parameters.

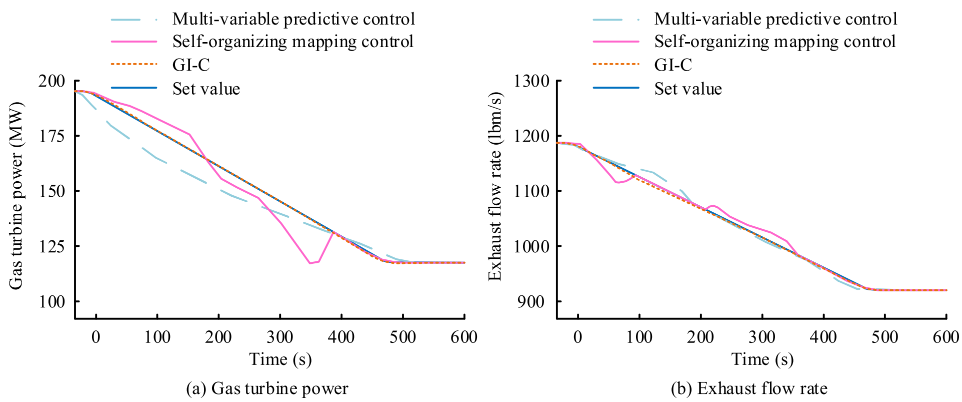

FIGURE 12. The change of controlled quantity when the load changes.

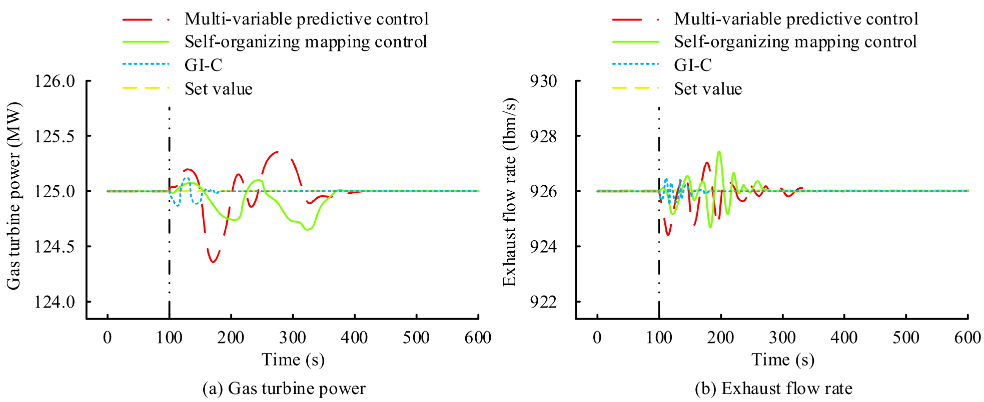

FIGURE 13. The change of the controlled quantity when the opening of the inlet guide vane is disturbed.

completely eliminates the fluctuation of the combustion engine power in more than 300s, and the maximum fluctuation reaches 0.7MW. The control result of the self-organizing mapping control technique completely eliminates the fluctuation of the combustion engine power in more than 300s, and the maximum fluctuation reaches 0.4MW. The control result of the GI-C completely eliminates the fluctuation of the combustion engine power in less than 100s, and the maximum fluctuation remains within 0.2MW. It takes less than 100s and the maximum fluctuation is kept within 0.2MW. In Figure 13(b), when EF is the controlled quantity, it takes more than 300s to completely eliminate the EF fluctuation by the multi-variable predictive control technique, and the maximum fluctuation reaches 1.8lbm/s. It takes about 180s to completely eliminate the EF fluctuation by the self-organizing mapping control technique, and the maximum fluctuation reaches 1.8lbm/s. The EF fluctuation is eliminated by the GI-C technique, with the maximum fluctuation being 0.7mw and the process taking 80s. The maximum fluctuation is 0.7 lbm/s. It demonstrates how the study

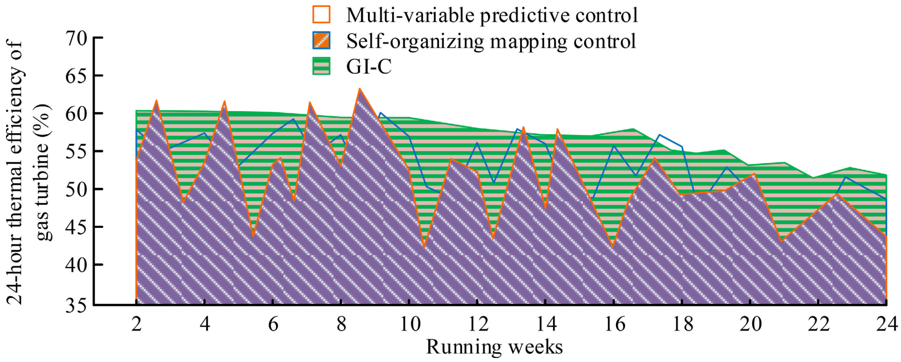

FIGURE 14. Thermal efficiency of 24h gas turbine.

methodology produces combustion engine control findings that can lessen the influence of external variations on stability while also more quickly eliminating their influence. The thermal efficiency of the 24h combustion engine is analyzed as shown in Figure 14.

In Figure 14, the different methods for generating the control strategy lead to different developmental patterns of the 24h combustion engine thermal efficiency when executed over a long period of time. The multi-variable predictive control technique control leads to the 24h combustion turbine thermal efficiency has a large fluctuation with a maximum of 63% and a minimum of only 42%. However, the overall 24h combustion turbine thermal efficiency showed a significant downward trend during the 24 weeks of operation. The self-organizing mapping control technique leads to small fluctuations in the 24h thermal efficiency, with a maximum of 60% and a minimum of 43% over the 24 weeks of operation. Long-term operation also resulted in a more significant thermal efficiency drop. The GI-C has a strong ability to control the stability of the 24h thermal efficiency of the combustion turbine in the long-term control without significant fluctuations. Long-term operation also demonstrates a decreasing trend. In the second week of the 24-hour thermal efficiency of the combustion engine, it reached 60%. After 24 weeks, the 24-hour thermal efficiency of the combustion engine decreased to 52%. Compared with the multi-variable predictive control technology and self-organizing mapping control technology, it has better stability and thermal efficiency retention ability. Compared to existing advanced particle swarm optimization algorithms and genetic algorithms, research methods require fewer parameters to be adjusted. Particle swarm optimization algorithm requires setting parameters for particle velocity and position updates, while genetic algorithm involves genetic operation parameters such as crossover rate and mutation rate. The main parameters of the research method include population size, maximum number of cycles, and maximum number of failures, and the adjustment of these parameters is relatively simple. When conducting calculations, the research method introduces the FA to handle large-scale multi-variate problems. Although the computational complexity increases with the size of the problem, its growth rate is relatively slow, and the overall iteration speed is also faster. For example, when the research method is trained on the fault dataset of the GT control system, the loss value drops to 0.023 by the time the iteration reaches 50 times. The FA clustering and covariance matrix calculation provide data support for the algorithm, enabling it to better adapt to the actual distribution of data.

IV. CONCLUSION

A CECT combining ABC and CA has been studied and designed to make an improvement in the work quality of the combustion engine. The process transforms the combustion engine model into a multi-input and multi-output system. It takes EF and combustion engine load as the system outputs, performs local non-linear weighting calculations to obtain the global output of the model, introduces FA to optimize the post-calculation stage of ABC, performs optimization on the control parameters of the combustion engine, uses clustering of FL as a means of clustering, and introduces the covariance matrix calculations to avoid the over-fitting condition. Finally, the research methodology is analyzed to determine its validity. The experimental results indicated that in the analysis of the ME of the EF model of the combustion engine, the ME of the EF model of the combustion engine by the research method was in the range of −1.7lbm/s to 2.9lbm/s. The ME of the EF model of the combustion engine by the research method was in the range of −2.7lbm/s to 2.9lbm/s. When the calculation time of the control parameters was analyzed, the calculation time of the research method was only 1121ms when the number of input data was 6000 in the two combustion turbines. In the analysis of the change of the controlled quantity when the OIGV was subjected to perturbation, the research method took less than 100s to eliminate the power fluctuation of the combustion turbine completely when the research method was carried out, and the maximal fluctuation was kept within 0.2 MW. It indicates that the research method has higher control accuracy of the combustion engine and can make the combustion engine enter the preset working state at a higher speed. However, the study does not consider the data misalignment caused by possible power fluctuations in the control system, and more external environmental disturbances will be added to the analysis in order to enrich the experimental results and optimize the research method, and to expand the scope of application of the research method.

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