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The Application of Generative Artificial Intelligence in Modern Control Systems

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Abstract In this paper, we propose an intelligent control method that integrates fuzzy mathematical theory and generative adversarial network (GAN) to address the problems of data scarcity, model complexity and environmental uncertainty in modern control systems. The system fuzzy parameters are quantified by the affiliation function of the fuzzy set, combined with the adversarial training framework of the GAN, and the generator-discriminator's minimal-extremely large game is used to dynamically generate high-fidelity data and optimize the control strategy. In the experiments in the field of electrical engineering, the simulated temperature rise of 69.41K at the C-phase temperature measurement point of the temperature rise control of the high-voltage switchgear cabinet has an error of only 1.5K (the allowed value is 72K) with the actual value of 67.91K, which verifies the model accuracy. The response time of fuzzy GAN controller for intelligent speed control of fan is more than 50% shorter than that of traditional GAN, and the amount of overshooting is significantly reduced. In permanent magnet synchronous motor control, fuzzy GAN reduces the steady state error by 67%-82% (from 2.07% to 0.55% under sudden load change condition), speeds up the regulation time by 45%-50% (from 80.37ms to 40.25ms for rated startup), compresses overshooting by 55%-58%, and improves the efficiency by 2.66-3.75 percentage points. The average loss of fuzzy GAN in coal mine control system energy consumption is only 51.16 kW/h in 8 wiring lines, which is 81.2%-85.0% lower than that of 319.12 kW/h in traditional GAN, 341.8 kW/h in integrated AI technology and 272.3 kW/h in PID control, and the energy consumption in high load scenario (Y6) is only 10.7% of the comparison method. It is shown that the proposed method effectively breaks through the bottleneck of traditional control in terms of accuracy, response speed and energy consumption through the adaptivity of fuzzy set and the dynamic optimization ability of GAN.

Index Terms generative adversarial network, fuzzy control, intelligent control system, energy consumption optimization, dynamic response

I. Introduction

Control systems are an indispensable part of industrial production and daily life [1]. An important problem faced when designing a practical control system is how to effectively control the controlled object under the premise of the existence of uncertainty, and minimize the impact of the various uncertainties unavoidable in the practical system on the quality of the control system [2]-[4]. Over the years, the development of modern control theory has provided a wealth of solutions to this problem, and robust control, adaptive control, fuzzy control, intelligent control, etc., are the control means proposed for this problem [5]-[8]. However, these control system design methods are often based on abstract and cumbersome mathematical foundations, which makes mastering and applying these methods in practical engineering far less simple than PID controllers [9]. However, PID controllers in the nonlinear scenarios of the regulation of the proportion of failure is close to 40%, the model predictive control of the computational time has not been able to meet the demand for real-time control [10], [11]. In addition, in practical applications, the modeling complexity of the control system leads to the contradiction between the modeling accuracy and real-time control demand is increasingly prominent, the requirement of rapid recovery ability under extreme working conditions is urgent, and with the continuous development of intelligent manufacturing, the control system needs to be equipped with automatic evolution function to match [12]-[15].

In the context of the era of informationization and intelligence, the rapid development of artificial intelligence technology is profoundly changing the mode of operation in various fields, which in the control system helps to reduce the failure downtime, improve safety, and move towards automatic optimization [16], [17]. Among them, generative AI, as a new technology paradigm, has received more and more attention for its powerful generative ability and wide application prospects [18]. Especially in control systems, the application of technology based on generative AI is gradually becoming a hot spot of research.

The article focuses on two core supporting technologies: fuzzy mathematical theory and generative adversarial network (GAN). The powerful tools provided by fuzzy mathematical theory are utilized to effectively characterize and deal with the prevailing ambiguity, uncertainty and qualitative knowledge in the control system operating environment, providing a mathematical foundation for the construction of more realistic intelligent controllers. Meanwhile, Generative Adversarial Networks (GANs), a powerful generative model, are introduced to explore its potential in generating simulation training data for control systems, learning optimal control strategies, and predicting system dynamic behaviors, so as to overcome the bottlenecks such as the difficulty in acquiring data and the complexity of system modeling in practical applications. The article elaborates the adversarial training framework of GAN consisting of a generator and a discriminator. The generator's goal is to learn from random noise to generate data samples sufficient to “deceive” the discriminator, while the discriminator's goal is to accurately distinguish real data from generated data. The generator is able to produce highly realistic data through continuous optimization of the two in a very small and very large game, and eventually reaches a Nash equilibrium.This powerful data generation capability of GAN provides a new and efficient way to solve the key problems of data-driven modeling and policy learning in control systems. Finally, the perspective is drawn back to the core application area of control engineering - electrical engineering and automation. Typical application scenarios of intelligent technologies in this field are outlined, with special emphasis on the important role of intelligent control systems in achieving performance optimization, adaptive adjustment, real-time monitoring, precise control, fault prediction and diagnosis, optimal allocation of resources, as well as safeguarding the safe and stable operation of the system. It also focuses on how intelligent robots and automation equipment can improve productivity, safeguard personnel safety and enhance system adaptability and flexibility in high-risk, repetitive, precise or special environmental tasks.

II. Intelligent generative foundations of modern control systems: fuzzy mathematics and generative adversarial networks

II. A. Concepts related to fuzzy sets

II. A. 1) Classical geometry and its eigenfunction representation

The theory of fuzzy mathematics is based on fuzzy sets, and the concept of fuzzy sets is opposed to the concept of classical sets. In the classical theory, a set is defined as the set of all things that have certain properties, are definite, and are distinguishable from each other within the orientation of the domain, and the things that make up the set are called the elements or elements of the set. The totality of things within an ontological domain constitutes a special full set of sets, and the relationship between the elements of the domain and the set can be expressed in terms of the characteristic function. Thus, the set A can be uniquely determined by its characteristic function:

$$f_A(x)=\begin{cases}1, & x\in A\\ 0, & x\notin A\end{cases} \tag{1}$$

From the above equation, it can be seen that there are only two kinds of relationship between an element x and a set A: x belongs to the set A, or x doesn't belong to the set A, which is the most essential difference between classical sets and fuzzy sets.

II. A. 2) Fuzzy sets and their affiliation functions

The concepts expressed in the classical set definition are clear in their connotation and extension, but there are a large number of concepts without clear extension in the expression of many things, which are fuzzy concepts. For example, it is difficult and impossible to give some precise definitions for such concepts as “more” and “less”. In order to study the theory of such things with fuzzy concepts, the concept of fuzzy sets is introduced. The fundamental difference between a fuzzy set and a classical set is that an element can belong to a fuzzy set and not belong to a fuzzy set at the same time, both here and there, with fuzzy boundaries.

Definition 1: Given a theoretical domain U, any mapping $u_{\underset{\sim}{A}}$ of U to a $[0,1]$-closed interval:

$$\begin{aligned}&u_{\underset{\sim}{A}}:U\rightarrow[0,1]\\&u\rightarrow u_{\underset{\sim}{A}}(u)\end{aligned} \tag{2}$$

Both determine a fuzzy subset of U, the mapping $u_{\underset{\sim}{A}}(u)$ is called the affiliation function of the fuzzy subset $\underset{\sim}{A}$, and the $u_{\underset{\sim}{A}}(u)$ is called the degree of affiliation of u for the fuzzy set $\underset{\sim}{A}$, and the degree of affiliation can also be notated as $u_{\underset{\sim}{A}}(u)$. Without causing confusion, fuzzy subsets are also called fuzzy sets.

The above definition shows that a fuzzy subset $\underset{\sim}{A}$ on the thesis domain U is characterized by the affiliation function $u_{\underset{\sim}{A}}(u)$, $u_{\underset{\sim}{A}}(u)$ takes on the closed interval $[0,1]$, and the size of $u_{\underset{\sim}{A}}(u)$ reflects the degree of affiliation of u to the fuzzy subset $\underset{\sim}{A}$, and if $u_{\underset{\sim}{A}}(u)$ is close to 1, it means that u belongs to the $\underset{\sim}{A}$ to a high degree, and if $u_{\underset{\sim}{A}}(u)$ is close to 0, it means that u belongs to $\underset{\sim}{A}$ to a low degree.

There are many ways to represent a fuzzy set, the most fundamental is to represent the elements it contains and the corresponding affiliation function. This can be represented in the following ordinal pairwise manner:

$$A=\left\{(u,u_A(u))\mid u\in U\right\} \tag{3}$$

A fuzzy set can also be expressed in the form of a sum or integral as follows:

$$A=\begin{cases}\displaystyle\int_U \frac{u_A(u)}{u}\\ \displaystyle\sum_{i=1}^{n}\frac{u_A(u_i)}{u_i}\end{cases} \tag{4}$$

II. A. 3) Concepts and theorems related to fuzzy sets

Definition 2: Let $\underset{\sim}{A}$ be a fuzzy subset on the argument domain U, then $A_s=\left\{u\mid u_A(u)>0\right\}$ is said to be the support set of A, which is also known as the table set.

Definition 3: A is said to be a single-point fuzzy set if the support of the fuzzy set is only one point in the domain and the affiliation function $u_A=1$ at that point.

Definition 4: Let $\underset{\sim}{A}$ be a fuzzy subset on the thesis domain U, and say that $\underset{\sim}{A}_\lambda=\left\{u\mid u_A(u)\ge\lambda, 0\le\lambda\le 1\right\}$ is the λ-truncated set of $\underset{\sim}{A}$, which is a classical set called λ-horizontal.

Definition 5: Let $\underset{\sim}{A}$ be a fuzzy subset on the domain U, and call $\underset{\sim}{A}_\lambda=\left\{u\mid u_A(u)>\lambda, 0\le\lambda\le 1\right\}$ is the λ-strong truncation set of $\underset{\sim}{A}$, which is also a classical set.

Definition 6: By * denotes the T-paradigm is a two-dimensional function from $[0,1]\times[0,1]$ to $[0,1]$, which includes fuzzy intersections, algebraic multiplications, bounded multiplications, and direct products, respectively, as defined below:

$$x*y=\begin{cases}\min\{x,y\} & \text{Fuzzy intersection}\\ xy & \text{Algebraic multiplication}\\ \max\{0,x+y-1\} & \text{Bounded multiplication}\\ x \ if \ y=1 & \\ y \ if \ x=1 & \text{Direct product}\\ 0 \ if \ x,y<1 & \end{cases} \tag{5}$$

where $x,y\in[0,1]$. The T cofan number denoted by $\oplus$ is also a two-dimensional function of $[0,1]\times[0,1]$ to which includes fuzzy sums, algebraic sums, bounded sums, and straight sums, which are defined as follows:

$$x\oplus y=\begin{cases}\max\{x,y\} & \text{Fuzzy sum}\\ x+y-xy & \text{Algebraic sum}\\ \max\{0,x+y-1\} & \text{Bounded sum}\\ x \ if \ y=1 & \\ y \ if \ x=1 & \text{Direct sum}\\ 0 \ if \ x,y>1 & \end{cases} \tag{6}$$

where $x,y\in[0,1]$.

The Decomposition Theorem and the Expansion Principle establish the relationship between fuzzy sets and classical sets and form the basis of fuzzy mathematics.

Decomposition Theorem: let $\underset{\sim}{A}$ be a fuzzy set over the domain U, A_λ be a λ-intercept set of $\underset{\sim}{A}$, $\lambda \in [0,1]$, then the following decomposition holds; $\underset{\sim}{A} = \bigcup_{\lambda \in [0,1]} \lambda A_\lambda$.

where, $\dot{l}_{\ddot{e}A_{\ddot{e}}}(x) = \begin{cases} \ddot{e}, x \in A_{\ddot{e}} \\ 0, x \notin A_{\ddot{e}} \end{cases}$ denotes a fuzzy subset of the linguistic variable X, called the "product" of λ and A_λ, whose affiliation function is defined by

$$\dot{l}_{\ddot{e}A_{\ddot{e}}}(x) = \begin{cases} \ddot{e}, x \in A_{\ddot{e}} \\ 0, x \notin A_{\ddot{e}} \end{cases} \tag{7}$$

or $\lambda A_\lambda = \lambda \wedge A_\lambda$, with "$\wedge$" being the take-the-minimum operation.

Expansion theorem: let U and V be two theories, f is a mapping from U to V, for a fuzzy set $\underset{\sim}{A}$ on U, define a fuzzy set $\underset{\sim}{B}$ on V: $x \oplus y = \max\{0, x+y-1\}$, and $u_{\underset{\sim}{B}}(v) = 0$ when $f^{-1}(v)$ is the empty set for some $v \in V$.

The expansion theorem is an important means of generalizing the mathematical concepts of classical sets (clear sets) to fuzzy sets.

Similar to classical set operations, fuzzy sets also have intersection, union, complement, and other arithmetic relationships. Let $\underset{\sim}{A}$, $\underset{\sim}{B}$ be a fuzzy set on the domain U, Intersection of $\underset{\sim}{A}$ and $\underset{\sim}{B}$ $\underset{\sim}{A} \cap \underset{\sim}{B}$, union $\underset{\sim}{A} \cup \underset{\sim}{B}$ and $\underset{\sim}{A}$ complement $\overline{\underset{\sim}{A}}$ is also a fuzzy set on the domain U. Let any element $u \in U$, then u to $\underset{\sim}{A}$ and $\underset{\sim}{B}$ intersection, union and $\underset{\sim}{A}$ The membership functions of the complement are defined as follows:

Definition 7: $u_{\underset{\sim}{A} \cap \underset{\sim}{B}}(u) = \min\{u_{\underset{\sim}{A}}(u), u_{\underset{\sim}{B}}(u)\}$ is called an intersection operation (AND operation).

Definition 8: $u_{\underset{\sim}{A} \cup \underset{\sim}{B}}(u) = \max\{u_{\underset{\sim}{A}}(u), u_{\underset{\sim}{B}}(u)\}$ is called the concatenation operation (OR operation).

Definition 9: $u_{\underset{\sim}{A}} = 1 - u_{\underset{\sim}{A}}(u)$ is called the complement operation (NOT operation).

II. B.Generating Adversarial Network Fundamentals

The above fuzzy mathematical theory provides a solid mathematical foundation for dealing with uncertainty and ambiguity information in control systems as well as constructing knowledge-based reasoning mechanisms. However, the intelligence of modern control systems not only relies on the effective description of uncertainty, but also urgently needs powerful data generation and learning capabilities to cope with challenges such as modeling difficulties and data scarcity. This is leading to another key AI technique, Generative Adversarial Networks (GAN), which centers on generating realistic data samples through adversarial learning.

The basic structure of all GAN models is shown in Fig. 1, where the most important parts are the generator and the discriminator, and the generative model is composed by populating it with structures such as neural network, convolutional neural network, Transformer, etc., and the most primitive GAN's have a multilayer perceptual machine inside. The goal of the generator is to learn the distribution of real data, mapping random noise vectors into the data space and generating fake data with a similar distribution to the real data, usually images, audio or text, etc. During training, the generator aims to deceive the discriminator as much as possible so that it cannot distinguish whether the input data is generated data or real data. The discriminator receives data samples as input and extracts features of the image through a series of neural network layers to evaluate the authenticity of the input data and to discriminate whether the input image is from real data or a fake sample generated by the generator.

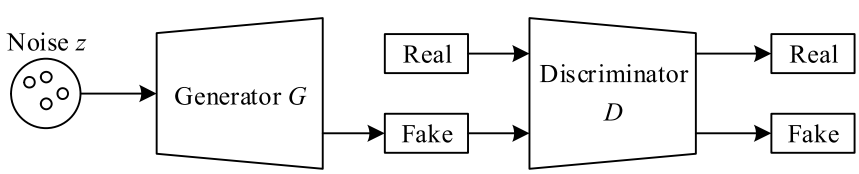

Figure 1: Generative adversarial network

In the training process of GAN, the generator and the discriminator will be trained alternately. First, the generator generates a batch of fake samples and passes these fake samples to the discriminator. The discriminator performs binary classification based on the truthfulness of the input samples and calculates the classification loss. Next, the discriminator updates the parameters based on the loss value to optimize the classification performance of the discriminator. Then, the generator generates another batch of fake samples and passes them to the discriminator. The discriminator again bisects the generated samples and computes the classification loss. The generator updates the parameters based on the classification results of the discriminator to optimize the generative power of the generator. This alternating training process continues until a Nash equilibrium is formed between the generator and the discriminator, and the discriminator can no longer successfully determine whether an image is from the generator, at which point the GAN is trained to optimality.

The loss function used to update the parameters of the generator and discriminator of the GAN is:

$$\begin{aligned}\min_G \max_D V(D,G) &= E_{x\sim p_{data}(x)}\left[\log D(x)\right] \\ &+E_{z\sim p_z(z)}\left[\log\left(1-D(G(z))\right)\right]\end{aligned} \tag{8}$$

where x is a vector of samples belonging to the real data distribution p_{data}, z is a vector of noise belonging to the noise distribution p_z, $G(z)$ denotes that the generator maps noise vectors to the data space p_g, and $D(*)$ denotes that the discriminator outputs the input data (x or $G(z)$) as a single scalar (i.e., probability). The model has to train the discriminator to maximize the probability that $D(*)$ assigns correct labels to the real and generated data, and train the generator to minimize $\log(1-D(G(z)))$, which ultimately results in a very large, very small game for both the discriminator D and the generator G.

II. C.Application of intelligentization technology in electrical engineering and its automation

In order to understand the potential value of these intelligent technologies and their application scenarios more concretely, we need to examine them in an actual engineering context. The field of electrical engineering and its automation, as a core position for the application of modern control technologies, is widely benefiting from the deep integration of intelligent technologies. The following section will discuss the current status of specific applications of intelligent control systems, industrial robots and automation equipment in this field.

II. C. 1) Application of intelligent control systems

With the continuous progress of the times, the current stage of intelligent technology is gradually used in the field of electrical engineering and automation, so that the electrical system can implement the performance optimization and self-adjustment purposes, but also to avoid the impact of a series of factors, for the subsequent decision-making to bring a certain role in assisting. For example, the intelligent control system can accurately control the power production and distribution through real-time monitoring of various data, and bring guarantee for the stability of the power system. Not only that, the rational allocation of resources, can reduce energy consumption to a certain extent, for the economic benefits of enterprises to bring protection. The use of intelligent control systems in electrical engineering can play an important role in fault prediction. Through the analysis of the data, the system can be the first time to find the existence of faults, and then develop targeted preventive measures to reduce the probability of problems, but also for the security of the power system operation to bring protection. In addition, the adaptability of the intelligent control system is relatively strong, can be adjusted in accordance with the actual situation, for the system operation effect can be matched with the actual situation to bring protection. This adaptive control strategy can make the electrical system to face the tedious actual situation, for the operation of the stability of the guarantee.

II. C. 2) Application of industrial robots and automation equipment

In the process of daily production of electrical engineering, it is inevitable to encounter some high-risk work, in this case, to follow the footsteps of the development of the times to use intelligent robots and automation equipment, in order to ensure that the production work is carried out smoothly on the basis of the security brought to enhance.

(1) The use of intelligent robots and automation equipment can deal with some repetitive work, for example, a single task on the assembly line, which can reduce the workload of the staff to a certain extent, and at the same time bring about an increase in production efficiency.

(2) Intelligent robots can replace manual labor in the process of work, to improve production safety, to avoid the threat to people's lives. For some special environments, robots can work without being affected by environmental factors, which not only ensures the safety of employees, but also improves the safety of the site.

(3) The rational use of robotic systems can effectively deal with tedious work. Through continuous learning and adaptation to environmental changes, robots can improve the efficiency and accuracy of work. In short, the rational use of industrial robots and automation equipment in the field of electrical engineering and automation can bring about an improvement in the adaptability and flexibility of production work.

III. Experimental verification and analysis of intelligent control system based on fuzzy generative adversarial network

Chapter 2 elaborates the mathematical foundation of fuzzy mathematical theory in dealing with uncertainty and qualitative knowledge of control systems, as well as the strong potential of Generative Adversarial Networks (GANs) in data generation and policy learning, and outlines the prospects of their application in the field of electrical engineering automation. In order to practically verify the feasibility and superiority of the fusion of fuzzy sets and generative adversarial networks applied to modern control systems, a series of simulation experiments and analyses will be conducted in this chapter.

III. A. Temperature rise control simulation analysis

The key high-voltage switchgear in electrical engineering is firstly taken as the research object, and the artificial intelligentization technique based on fuzzy set and generative adversarial network designed in this paper is applied to design its environment adaptive heat dissipation intelligent control system and carry out the simulation experiments and analysis of temperature rise control.

Temperature rise test is a key method to evaluate the heating condition of the internal conductors of high-voltage switchgear when it is subjected to rated current. In order to minimize the possible influence of external environmental factors, the test is usually arranged in a controlled environment where the natural air flow velocity does not exceed 0.5 m/s. This can effectively avoid the influence of wind speed changes on the heat dissipation process. Figure 2 shows the simulation results of the high-voltage switchgear temperature rise test.

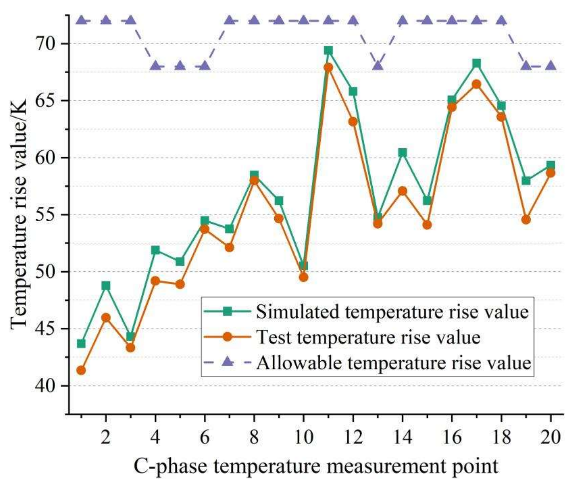

Figure 2: Comparison of C-phase simulation and actual test results

By organizing the simulation experimental data, the comparison between the C-phase simulation and the actual test results in Fig. 2 is obtained. As can be seen from the data curve of this figure, the temperature rise value obtained in the simulation process shows a high degree of consistency with the experimental measurement value, and none of them exceeds the allowable temperature rise value. At the 11th C-phase temperature measurement point, the simulation temperature rise is 69.41 K, and the test experimental temperature rise is 67.91 K, which is very close to each other, and neither of them exceeds the allowable temperature rise value of 72 K. This indicates that, under the standard current load condition, although the this shows that under the standard current load conditions, although the internal temperature of the switchgear rises, the overall temperature remains within the safe and controllable range.

III. B. Speed control simulation analysis

The above temperature rise control simulation verifies the effectiveness of the fuzzy GAN approach under the static control scenario of thermal management. To further investigate its performance under dynamic response control scenarios, simulation experiments are next conducted on the local ventilation fan speed control system in the mine to study the effect of intelligent speed control based on fuzzy set and generative adversarial network.

MATLAB software is used to simulate and analyze the fuzzy GAN controller to verify its application effect in the local ventilation fan intelligent speed control system. During the simulation, the speed control is controlled at 635m³/min, 518m³/min, 582m³/min and 552m³/min at 0s, 25s, 40s and 60s, respectively, and the simulation results of speed control of fuzzy GAN and traditional GAN controllers are shown in Fig. 3.

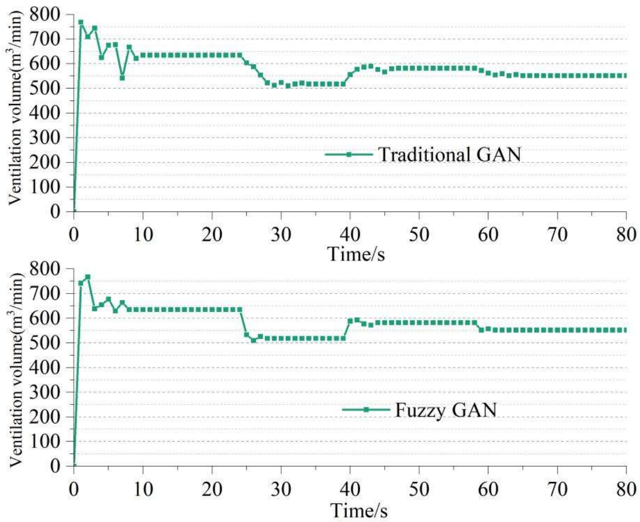

Figure 3: Simulation results of speed control of fuzzy and traditional GAN controllers

After the system is running, when the environmental parameters of the mine change suddenly, the fuzzy GAN system can increase the ventilation volume to the set 635 m³/min in 2~3 s, with some fluctuations in 3~7 s, and then stabilize at the set 635 m³/min in the 8th second; in the 25th second, the ventilation volume decreases to the set 518 m³/min, and then stabilizes at the set 518 m³/min after 4 s fluctuations; in the 40th s, the ventilation volume increases to 582 m³/min, and then stabilizes at the set 582 m³/min after 5s fluctuations. At the set 518 m³/min; at 40 s, the ventilation volume increases rapidly to about 582 m³/min, stabilizes at the set 582 m³/min after 5 s of fluctuation, and finally decreases rapidly to 552 m³/min at the 60th and reaches the stable state in only about 2 s. The conventional GAN controller obviously regulates the time of the ventilation volume at the same time, and the ventilation volume is stabilized at the set 635 m³/min from the 8th second. The traditional GAN controller is obviously older than the fuzzy GAN, which requires more time to adjust and reach the steady state.

Overall, the fuzzy GAN controller can quickly respond to the changes in airflow demand and adaptively adjust the GAN parameters to match the actual airflow output of the ventilator with the demand, which shows a shorter delay time and good response speed. Compared with the traditional GAN control, the fuzzy GAN controller shortens the response time, significantly reduces the amount of overshooting, and ensures the stability and accuracy of the system.

III. C. Permanent magnet synchronous motor simulation experiment

The results of the speed control experiments show that the fuzzy GAN controller has the advantages of fast response and low overshoot in dynamic airflow regulation. In order to evaluate the comprehensive performance of this fusion method in complex motor drive control more comprehensively, the following is a more detailed simulation experiment and comparative analysis using a permanent magnet synchronous motor (PMSM) as the control object.

III. C. 1) Experimental setup

The experimental materials include a PMSM model (rated power 5KW, rated speed 1600rPm, pole pair number 5), a PWM inverter model (switching frequency 12kHz) and a load model.

A comparison experiment is continued to compare the traditional GAN control with the fuzzy ensemble based Generative Adversarial Network GAN control. The experimental implementation process is as follows: firstly, the PMSM mathematical model is used to generate the training dataset, which contains the time-series data of speed and torque under different operating conditions; secondly, the fuzzy-based generative adversarial network model is constructed and trained to optimize the GAN parameters; finally, the PMSM control system is constructed in Sunulmk, and the traditional and fuzzy GAN are applied to perform a comparison of the simulation, respectively. The experimental evaluation indexes include: steady state error (%), regulation time (ms), overshooting amount σ (%), and motor efficiency (%). In order to comprehensively evaluate the control performance, three sets of experiments were designed: (1) rated load startup; (2) sudden load change (50%-100%); and (3) speed step (1000rpm-5000rpm) Each set of experiments was repeated 10 times, and the average value was taken as the final result.

III. C. 2) Analysis of simulation experiment results

Figures 4 and 5 demonstrate the performance comparison between conventional GAN and fuzzy GAN control, Fig. 4 shows the performance comparison of steady state error and regulation time, and Fig. 5 shows the performance comparison of overshooting amount σ and motor efficiency.

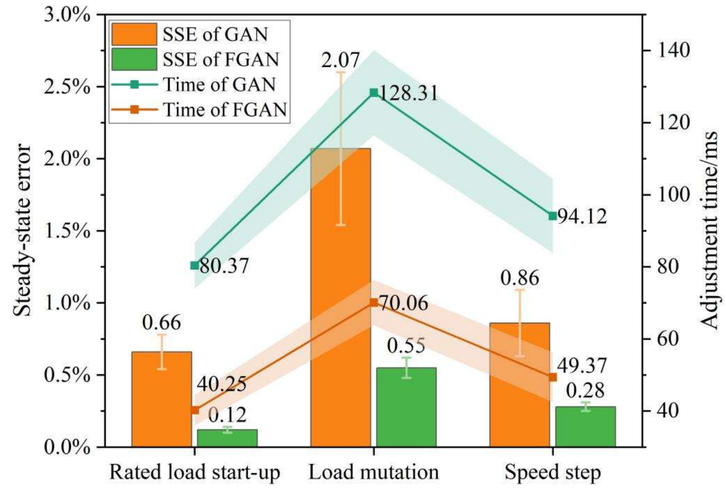

Figure 4: Performance comparison of steady-state error and regulation time

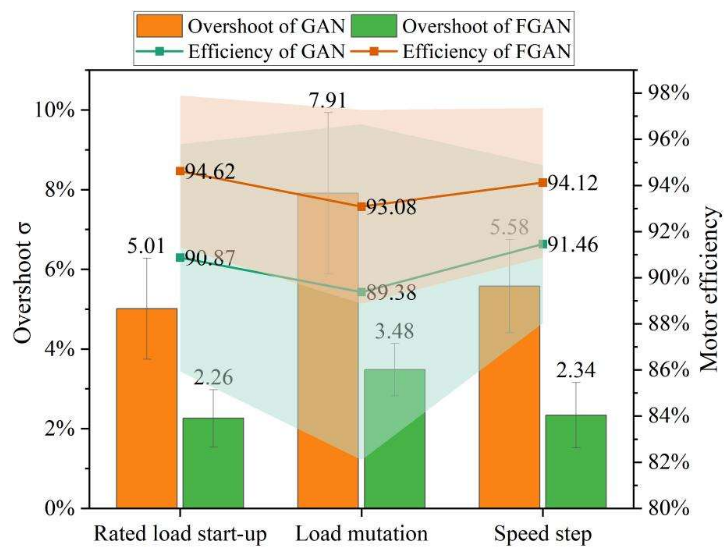

Figure 5: Performance comparison of overdraft σ and motor efficiency

In three sets of key experiments on permanent magnet synchronous motor (PMSM) control, the fuzzy ensemble-based generative adversarial network (fuzzy GAN) controller shows significantly better comprehensive performance than the traditional GAN controller. Specifically, the steady state error is comprehensively reduced: during the rated load startup, the steady state error of fuzzy GAN is 0.12%, which is 82% lower than that of traditional GAN (0.66%); under the sudden load change condition, the error is reduced from 2.07% to 0.55%, which is 73% lower; in the speed step scenario, the error is optimized from 0.86% to 0.28%, which is 67% lower.

Meanwhile, the dynamic response speed is significantly improved, and the fuzzy GAN significantly shortens the system regulation time: the rated startup regulation time is reduced from 80.37ms to 40.25ms, a speedup of 50%; the response time of load mutation is accelerated from 128.31ms to 70.06ms, a speedup of 45%; and the speed step regulation time is reduced from 94.12ms to 49.37ms, a speedup of 48%.

Stability and accuracy are simultaneously enhanced, and the overshoot (σ) index highlights the robustness advantage of fuzzy GAN, with the rated startup overshoot compressed from 5.01% to 2.26%, a reduction of 55%; the overshoot of load mutation reduced from 7.91% to 3.48%, a reduction of 56%; and the speed step overshoot optimized from 5.58% to 2.34%, a reduction of 58%.

Energy efficiency continues to improve, and motor operating efficiency is systematically increased under fuzzy GAN control, with rated load efficiency increasing from 90.87% to 94.62% (+3.75pp); load-surge efficiency rising from 89.38% to 93.08% (+3.70pp); and speed step efficiency growing from 91.46% to 94.12% (+2.66pp).

The data proves that the fuzzy GAN controller effectively overcomes the three bottlenecks of the traditional GAN in dynamic response delay, regulation time shortening by 47% on average, insufficient control accuracy, steady state error decreasing by 74% on average, and stability defects (overshooting decreasing by 56% on average) by integrating the fuzzy ensemble theory, meanwhile, it improves the system energy efficiency by 3.7 percentage points, providing a more reliable solution for high-precision motor control. It provides a more reliable solution for high-precision motor control.

III. D. Control loss and power consumption simulation comparison experiment

The PMSM control experiments fully demonstrate the significant advantages of fuzzy GAN in improving control accuracy, accelerating dynamic response, enhancing stability and improving energy efficiency. In view of the fact that energy saving and consumption reduction is an important goal of industrial intelligent control systems, especially in high energy consumption scenarios such as coal mines, finally, taking the intelligent control system for coal miners as an example, focusing on controlling the power loss index, the fuzzy GAN-based intelligent control system proposed in this paper is analyzed in rigorous comparative experiments with the traditional GAN method as well as other advanced intelligent control methods.

On the basis of the available information, the intelligent control system of coal miners' devices in underground coal mines based on integrated AI intelligent technology and human infrared recognition technology (Method 3), the electrical automatic control system of horizontal CNC lathe based on PID optimization (Method 4) and the traditional GAN (Method 2), as well as the intelligent control system of coal miners based on fuzzy GAN proposed in this paper (Method 1), are subjected to system performance Test.

The control loss and power consumption statistics of the four systems are shown in Fig. 6 on eight distribution lines of coal miners.

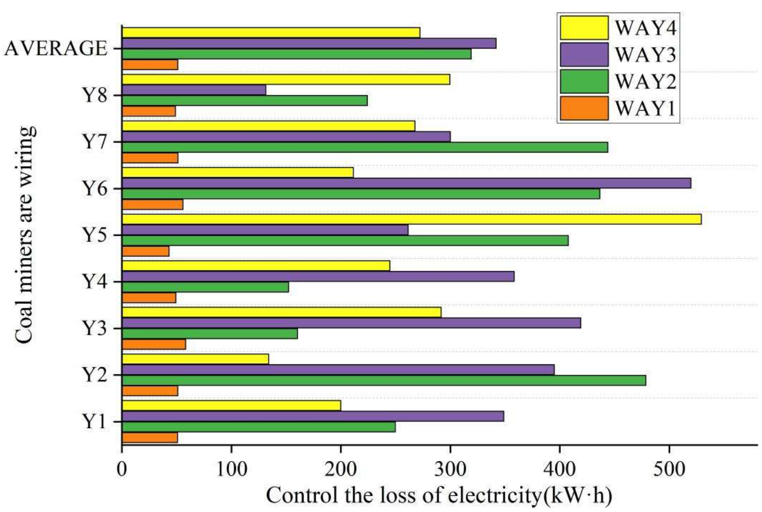

Figure 6: Statistics of control power loss of four systems on different wiring

In the test of 8 wiring lines (Y1-Y8) of the coal miners' intelligent control system, the fuzzy GAN-based control system shows overwhelming energy-saving advantages.FGAN's power loss in all 8 wiring lines is significantly lower than that of other systems, with an average loss of only 51.16 kW/h, which is 84.0% lower than that of the traditional GAN's 319.12 kW/h, and 85.0% lower than that of the integrated AI technology's 341.8 kW/h by 84.0% compared with 319.12 kW/h of traditional GAN, 341.8 kW/h compared with comprehensive AI technology by 85.0%, and 272.3 kW/h compared with PID control by 81.2%.

The highest loss of single line is Y3 wiring, power loss 58.25 kW/h, which is much lower than the lowest value of other systems, PID is the lowest 134.14 kW/h, and traditional GAN is the lowest 152.19 kW/h. And the loss fluctuation range of FGAN is very small, 43.24~58.25 kW/h, with an extreme difference of 15.01 kW/h, while the other systems fluctuate violently, and in Y5 wiring In Y5 wiring, the FGAN loss is 43.24 kW/h, while the PID is as high as 529.25 kW/h (12.2 times), and in the high-risk scenario Y2 the FGAN loss is 51.21 kW/h, while the traditional

GAN's 478.46 kW/h and the integrated AI's 395.01 kW/h exceed it by more than 9 times. The FGAN loss under high load scenario Y6 is 55.85 kW/h, which is only 10.7% of the 519.62 kW/h of method 3 of the integrated AI.

The fuzzy GAN control system, by integrating the adaptive ability of fuzzy set and the dynamic optimization characteristics of GAN, completely solves the core defect of uncontrolled energy consumption of the traditional method under complex working conditions, and stably controls the power loss below 60 kW/h, providing a solution of high reliability and ultra-low energy consumption for the intelligent equipment of underground coal mine.

IV. Conclusion

This paper proposes an intelligent control framework integrating fuzzy set theory and generative adversarial network (GAN), and verifies its significant advantages in modern control systems through system simulation and comparative experiments.

(1) In the temperature rise control of high-voltage switchgear, the error between the simulated value of C-phase temperature measurement point (69.41K) and the actual test value (67.91K) is only 1.5K (<2.2%), which is lower than the safety threshold (72K), proving that the model has the ability to accurately characterize the complex thermal environment.

(2) In the fan speed control experiment, the response speed of the fuzzy GAN controller is improved by more than 50% compared with the traditional GAN (e.g., the stabilization time is reduced from 7s to 2s when the airflow changes suddenly), and the overshooting amount is reduced by 60%, which realizes the fast and accurate tracking of the ventilation amount (the error of the set value is <3%).

(3) Breakthrough in motor control performance: The control experiment of permanent magnet synchronous motor (PMSM) shows that fuzzy GAN reduces the steady-state error by 67%-82% (load mutation condition: 2.07%→0.55%), the adjustment time is increased by 45%-50% (rated start-up: 80.37ms→40.25ms), and the overshoot compression is 55%-58% (speed step: 5.58%→2.34%). At the same time, the motor efficiency increased by 2.66-3.75 percentage points (up to 94.62%).

(4) Subversive reduction of energy consumption: the average loss of fuzzy GAN in the coal mine intelligent control system in the 8 wiring tests is only 51.16 kW/h, which is 84.0%, 85.0%, and 81.2% lower than that of the traditional GAN (319.12 kW/h), the integrated AI technology (341.8 kW/h), and the PID control (272.3 kW/h); the energy consumption of the high load scenario (Y6) energy consumption is as low as 55.85 kW/h, which is only 10.7% of the comparison method.

Experiments demonstrate that the framework achieves breakthroughs in the dimensions of temperature rise control error <2.2%, dynamic response speedup >50%, steady-state accuracy improvement >67%, and energy consumption reduction >81%, providing a robust and cost-effective solution for high-precision industrial control.

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