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Research on PID Control Strategy for Mine Air Conditioning Systems Based on Interval Type-2 Fuzzy Neural Network

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***Abstract*— *High-temperature thermal damage in underground mines remains one of the critical bottlenecks restricting deep resource exploitation, posing severe threats to miner safety and equipment reliability. Conventional PID controllers exhibit insufficient adaptability when dealing with the nonlinearity, time-varying dynamics, and strong disturbances characteristic of mine temperature fields. To address these challenges, this paper proposes an optimized temperature control algorithm for mine air conditioning systems based on an Interval Type-2 Fuzzy Neural Network PID (IT2FNN-PID) controller. The proposed algorithm integrates the dynamic uncertainty compensation capability of interval type-2 fuzzy logic with the self-learning mechanism of neural networks, enabling real-time online tuning of PID parameters. A simplified thermodynamic model of the mine environment is first established to construct the transfer function of the temperature control system, with comprehensive analysis of multi-source disturbances including heat sources and surrounding rock heat dissipation. An interval type-2 fuzzy rule base with adaptive membership functions is then designed, and the inference parameters are dynamically optimized through the neural network structure. Comparative simulations are conducted using Matlab/Simulink, evaluating conventional PID, type-1 fuzzy PID (T1F-PID), interval type-2 fuzzy PID (IT2F-PID), and the proposed IT2FNN-PID controllers. Simulation results demonstrate that the IT2FNN-PID controller outperforms the other methods in terms of overshoot reduction, response speed, and steady-state accuracy, exhibiting superior robustness and environmental adaptability in mine temperature regulation applications.*

***Keywords*—Interval Type-2 Fuzzy Logic; Neural Network; PID Control; Mine Air Conditioning; Temperature Control**

I. INTRODUCTION

As shallow mineral resources are progressively depleted, deep mining (with burial depths exceeding 1000 m) has become an inevitable trend in the mining industry. However, the geothermal gradient effect causes a sharp increase in underground mine temperatures, giving rise to severe thermal damage problems. According to the *China Mine Safety Development Report (2023)*, approximately 52% of deep mine working faces in China experience temperatures exceeding 35 °C, with annual direct economic losses attributed to thermal damage reaching as high as 7.8 billion RMB. Elevated temperatures not only exacerbate heat stress responses among miners—triggering health issues such as heatstroke and cardiovascular diseases—but also increase equipment failure rates by more than 30%. In some ultra-deep mines, nearly 30% of recoverable resources have been abandoned due to extreme thermal conditions. Consequently, the development of efficient and robust mine temperature control systems holds substantial engineering significance and socio-economic value.

The underground mine thermal environment is a typical nonlinear, strongly coupled, and multi-disturbance system. Multiple factors—including surrounding rock heat transfer, heat generation from electromechanical equipment, and sudden variations in ventilation airflow—interact with one another, causing the temperature field to exhibit significant time-varying uncertainty and spatial heterogeneity [1]. Conventional temperature control technologies have largely relied on mechanical refrigeration combined with manually tuned proportional-integral-derivative (PID) controllers. Although PID control is structurally simple and straightforward to implement, its parameters are fixed once tuned, making it difficult to adapt to the dynamic changes in downhole operating conditions. In practice, this often manifests as sluggish response, excessive overshoot, and poor disturbance rejection [2].

To overcome the limitations of conventional PID controllers, intelligent control strategies have become a research hotspot in recent years. Among these, fuzzy PID control introduces nonlinear mapping capabilities into the controller by emulating expert experience, thereby improving adaptability to uncertainties to a certain extent. However, conventional type-1 fuzzy PID (T1F-PID) controllers employ precise membership functions, which are inadequate for capturing the inherent uncertainties arising from the coupling of multi-source information such as downhole temperature, humidity, and airflow velocity [3]. To address this issue, Zadeh proposed the theory of type-2 fuzzy sets in 1975. In particular, interval type-2 fuzzy sets (IT2FS), which offer superior computational efficiency, introduce the concept of "footprint of uncertainty" (FOU) and can more effectively model and handle higher-order uncertainties [4]. In recent years, interval type-2 fuzzy PID (IT2F-PID) controllers have demonstrated superior robustness compared to T1F-PID in various industrial applications [5][6].

Furthermore, by integrating the learning capability of neural networks with interval type-2 fuzzy logic, the interval type-2 fuzzy neural network PID (IT2FNN-PID) controller has been developed, enabling online self-organization of fuzzy rules and dynamic self-tuning of PID parameters [7][8]. In international research, Hagras and his team proposed a hierarchical IT2FNN-PID architecture that significantly reduced overshoot in temperature control of chemical reactors. Liu et al. simplified the rule base using α-plane decomposition, thereby improving real-time computational efficiency [9]. In domestic research, Chen and Lin applied IT2FNN to nonlinear system control, effectively mitigating signal noise and time-varying parameters [3]; Wang et al. designed an adaptive fuzzy PID controller for mine ventilation systems, achieving substantial reduction in steady-state error [4]. Nevertheless, the application of IT2FNN-PID to precise temperature field control in mine environments characterized by high humidity, high temperature, and multiple disturbances—including system modeling, controller design, and performance validation—remains an area requiring further investigation.

Despite the promising results reported in existing studies, several critical issues remain unresolved regarding the application of IT2FNN-PID to mine temperature control: (1) the lack of a simplified yet practically meaningful thermodynamic model specifically tailored to mine cooling scenarios, balancing engineering feasibility with theoretical accuracy; (2) the scarcity of systematic comparative studies evaluating different control strategies under unified operating conditions, making it difficult to quantitatively assess the actual performance differences among various approaches.

To address these research gaps, the main contributions of this paper are threefold: (1) A simplified thermodynamic transfer function model is established for mine temperature control scenarios, incorporating the dynamic characteristics of the main ventilation fan and the primary thermal disturbances. (2) Four controllers—conventional PID, T1F-PID, IT2F-PID, and IT2FNN-PID—are systematically designed, with detailed elaboration on the construction of interval type-2 fuzzy membership functions and the neural-network-based parameter optimization layer. (3) Multi-controller comparative simulations are conducted using Matlab/Simulink, evaluating the performance of each strategy through quantitative metrics including overshoot, peak time, settling time, and steady-state error, thereby validating the superiority of IT2FNN-PID in mine temperature control applications.

The remainder of this paper is organized as follows: Section 2 presents the simplified thermodynamic model of the mine environment and the transfer function of the temperature control system. Section 3 elaborates on the architectural design and parameter optimization methodology of the IT2FNN-PID controller. Section 4 describes the simulation platform configuration and the comparative experimental scheme. Section 5 presents and discusses the simulation results. Section 6 concludes the paper with a summary of findings and recommendations for future work.

II. THEORETICAL FOUNDATIONS OF PID AND FUZZY CONTROL

The PID controller corrects system deviations by linearly combining the regulating effects of proportional (P), integral (I), and derivative (D) components. Its continuous-time domain expression is:

$$u(t) = K_P e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{1}$$

where e(t) represents the deviation between the set value and the actual output, and Kp, Ki, Kd stand for the proportional, integral, and derivative coefficients, respectively. In digital control systems, position-type or incremental-type PID algorithms are commonly used for implementation:

Positional PID:

$$u(t) = K_P e(t) + K_i T \sum_{i=0}^{k} e(i) + K_d \frac{e(k) - e(k-1)}{T} \tag{2}$$

Incremental PID (widely used in actuator control):

$$\Delta u(k) = K_P[e(k) - e(k-1)] + K_i T e(k) + K_d \frac{e(k) - 2e(k-1) + e(k-2)}{T} \tag{3}$$

Traditional PID has limited adaptability to nonlinear and time-varying systems, which has led to the emergence of improved versions such as adaptive PID and intelligent PID. The IT2FNN-PID in this study falls under the category of intelligent digital PID. The type 1 Fuzzy Controller (T1FC) maps precise inputs (such as temperature error e) to fuzzy values on the [0,1] interval through a membership function, simulating human linguistic concepts such as "approximately" and "slightly larger". Its typical structure includes four modules: fuzzification, rule base, fuzzy inference, and defuzzification. Common membership functions include Gaussian, triangular, trapezoidal, and so on. However, the membership grade of T1FC is a precise value, which cannot express the "fuzzy nature of the membership grade itself". The Interval Type-2 Fuzzy Controller (IT2FC) addresses this issue, where the membership grade of each element is an interval $[\underline{\mu}(x),\bar{\mu}(x)]$, and this interval range represents the Fuzzy Outcome Uncertainty (FOU). As shown in Fig. 1, for the concept of "old age", Type-1 fuzzy gives a precise curve, while Interval Type-2 fuzzy gives a region with upper and lower bounds, which can better accommodate group cognitive differences or environmental noise. This characteristic makes IT2FC more robust in dealing with highly uncertain systems such as mine temperature.

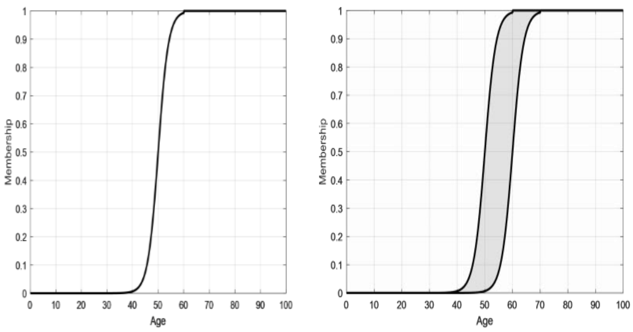

Figure 1: Schematic diagram of comparison between type 1 and interval type 2 membership degrees

IT2FNN-PID integrates the nonlinear fault-tolerant capability of IT2FC with the adaptive learning ability of neural networks. Its core architecture includes: (1) Interval Type-2 Fuzzy Inference Engine: It employs a dual-boundary membership function to handle the uncertainty of input variables and conducts inference through interval-based rule bases. (2) Neural Network Parameter Optimization Layer: It utilizes backpropagation or gradient descent to update the consequent parameters of fuzzy rules and membership function parameters online, thereby dynamically adjusting the three gain coefficients (Kp, Ki, Kd) of the PID controller. (3) PID Control Module: It calculates the control input in real-time based on the optimized parameters. Through this collaborative mechanism, IT2FNN-PID can handle parameter perturbations and sudden disturbances in the mine thermal environment, achieving high-precision and fast-response temperature control.

According to the "Coal Mine Safety Regulations", the air temperature at the mining and excavation workface should be strictly controlled below 26℃. The system needs to be compatible with three operation modes: manual, automatic, and automatic-manual. Traditional PID temperature control has poor performance, so this paper establishes the following simplified model. Based on the fuzzy PID controller, this system incorporates an interval type-2 fuzzy inference layer and a neural network parameter dynamic optimization layer. Its transfer function needs to be constructed in modules to achieve precise characterization. The mathematical model of the main fan in a mine can be regarded as the mathematical model of an asynchronous motor and a frequency converter:

$$G(s) = \frac{K_{MA}}{T_{MA}S + 1} \cdot \frac{K_S}{T_S + 1} \quad (4)$$

This model characterizes the second-order inertial characteristics between the fan speed and the variable frequency input. Where KMA is the ratio of the rated speed of the motor to the input frequency; TMA is the time constant, set to 0.25tp; tp is the motor starting time, set to 0.8s; s is the variable symbol in the transfer function; Ks is the ratio of the rated frequency of the frequency converter to the input voltage; Ts is the delay time, set to 0.6τ (τ is the acceleration time). In summary, the mathematical model of the main fan in a mine is as follows:

$$G(s) = \frac{20}{0.04s^2 + 6s + 1} \quad (5)$$

After considering the dynamic characteristics of the controller, the system can be approximated as a cascaded structure: GIT 2_PID = Kp. Kd is the time-varying parameter PID transfer function; H(s) is the sensor feedback channel model;

Using the classic PID structure, the parameters were initially tuned using the Ziegler-Nichols method and then fine-tuned through simulation, with the final settings being: Kp=4, Ki=10, Kd=0.001. A Transport Delay module with a delay time of 0.005s was added to the system output to simulate the actual delay between sensors and actuators.

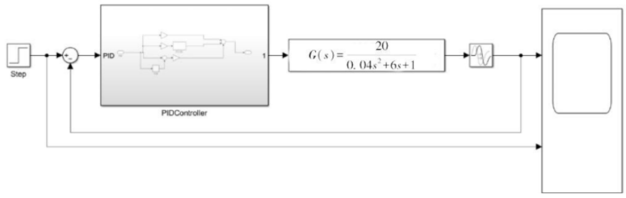

Figure 2: Simulink simulation block diagram of traditional PID controller

Input/output universe and membership function: The universes of input e and ec are both [-6,6], divided into 7 fuzzy sets: NB, NM, NS, ZO, PS, PM, PB. Gaussian membership function (gaussmf) is adopted. The universes of output ΔKp, ΔKi, ΔKd are set to [1,3], [1,3], and [0.5,2] respectively, also using Gaussian membership function.

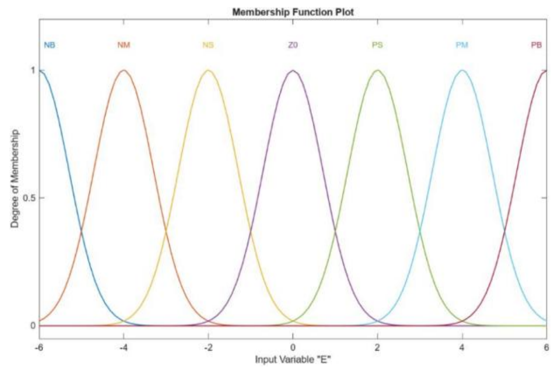

Figure 3: The membership function diagram of input variable e in Type 1 fuzzy PID

III. SIMULATION AND PERFORMANCE ANALYSIS

To fairly compare the dynamic performance of four controllers, a unified platform was established in Simulink for step response testing. The target temperature was set at 25℃, and the input was a unit step signal. Simultaneously, a simulated thermal disturbance (a pulse disturbance with an amplitude of 2) was introduced after 5 seconds of simulation time to observe the anti-disturbance capability of each controller.

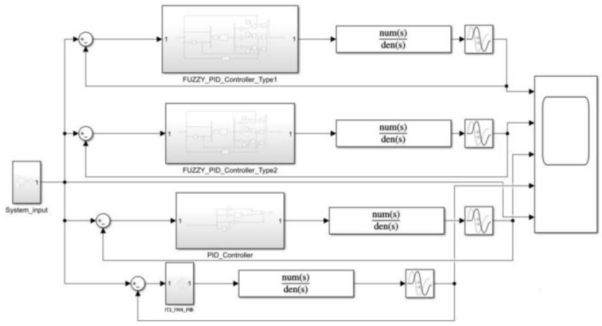

Figure 4: Simulation block diagram for comprehensive comparison of four controllers

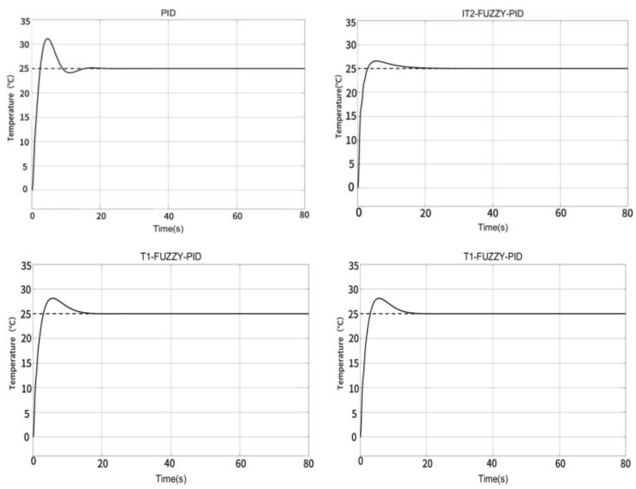

Figure 5: Step response curves of four types of control

IV. CONCLUSION

This study addresses the temperature control problem in mine cooling systems characterized by time-varying uncertainties and strong nonlinearities by proposing an interval type-2 fuzzy neural network PID (IT2FNN-PID) control strategy. Through comparative simulations on the Matlab/Simulink platform, the proposed method is evaluated against conventional PID, type-1 fuzzy PID (T1F-PID), and interval type-2 fuzzy PID (IT2F-PID) controllers. The results demonstrate that the IT2FNN-PID controller achieves superior dynamic parameter optimization through its self-designed fuzzy rule base, overcoming the limitations of manual tuning inherent in conventional PID control, while its refined capability to process multi-dimensional fuzzy information significantly outperforms the other methods in terms of robustness and environmental adaptability, validating its engineering feasibility for complex strongly coupled systems. Moreover, the proposed strategy achieves notable technical breakthroughs in control accuracy improvement, dynamic response acceleration, and temperature oscillation suppression compared to natural ventilation approaches. Future work will focus on further enhancing system performance through iterative upgrades in downhole sensor precision and integration of additional environmental parameters for practical engineering applications.

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