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Original Article

A Hybrid CNN-RNN-MRAC Deep Learning Framework for Adaptive Control of Intelligent Oxygen Generation Systems

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Abstract:
This paper presents a hybrid intelligent control framework for oxygen generation systems that integrates a Convolutional Neural Network (CNN), a Recurrent Neural Network (RNN), and Model Reference Adaptive Control (MRAC). The CNN extracts spatial correlations from multi-sensor inputs, the RNN, implemented with LSTM or GRU units, captures temporal dynamics in flow rate, pressure, and environmental variables, and the MRAC module enables real-time parameter adaptation under time-varying operating conditions. The proposed architecture is implemented and validated on a commercial molecular-sieve oxygen concentrator based on Pressure Swing Adsorption (PSA) technology. Experimental results show clear improvements over conventional PID controllers and single-branch deep-learning approaches: oxygen flow control accuracy within ±1.3%, oxygen concentration control accuracy within ±1.5%, and an average pressure fluctuation rate of 9.75%. These results indicate that the system can provide efficient and adaptive oxygen therapy, which is important for medical, aerospace, and home-care applications.
Keywords: Deep learning; convolutional neural network (CNN); recurrent neural network (RNN); model reference adaptive control (MRAC); intelligent control; oxygen concentrator; pressure swing adsorption (PSA)

1. Introduction

Oxygen therapy plays an important role in clinical medicine, high-altitude operations, aviation, and home care. Among available technologies, molecular-sieve oxygen concentrators based on Pressure Swing Adsorption (PSA) or Vacuum PSA (VPSA) have become a mainstream solution due to their compact size, safety, and energy efficiency. However, traditional control strategies—especially fixed-gain proportional-integral-derivative (PID) controllers—often fail to handle system nonlinearities, time-varying user demand, and environmental disturbances. As a result, oxygen purity can degrade, flow can become unstable, and power consumption can increase.

Recent advances in artificial intelligence, particularly deep learning, provide effective tools for modeling and controlling complex dynamical systems. Neural networks can learn hierarchical representations from raw sensor data and adapt to nonstationary environments. Although prior studies have explored fuzzy logic, reinforcement learning, and standalone neural models for oxygen delivery optimization, a unified framework that jointly combines spatiotemporal feature learning with theoretically grounded adaptive control remains under-explored.

To address this gap, we propose a hybrid CNN–RNN–MRAC control architecture for intelligent oxygen generators. Specifically:

- The CNN processes multi-sensor arrays arranged as 2D spatiotemporal tensors to capture cross-channel dependencies.
- The RNN (LSTM/GRU) models long-term temporal evolution in gas dynamics.
- The MRAC layer provides Lyapunov-stable real-time compensation to support asymptotic tracking of a predefined reference model.

The main contributions of this work are as follows:

1. A deep-learning–adaptive-control fusion architecture designed for oxygen generation systems.
2. End-to-end implementation and experimental validation on a commercial platform.
3. Benchmarking results showing improved control accuracy and stability compared with traditional PID and single-branch deep-learning baselines.

2. Related Work

Early oxygen concentrators relied on rule-based or PID-type controllers to regulate adsorption/desorption cycles and maintain output concentration [6]. With the advent of embedded sensing and IoT connectivity, data-driven control strategies have gained increasing attention [1].

Machine learning techniques have recently been applied to enhance oxygen delivery. Almeida et al. [4] employed LSTM networks within a digital twin framework to enable fault-tolerant operation, while Kumar et al. [5] combined fuzzy inference with online neural tuning to stabilize oxygen concentration. Smith and Chen [3] demonstrated deep reinforcement learning for personalized flow adaptation in portable concentrators, and federated GRU models have been investigated for distributed oxygen demand forecasting in clinical settings [4].

3. Methodology

3.1 System Architecture

The proposed controller comprises three tightly integrated modules (Fig. 1):

CNN Branch: Treats normalized sensor data as a 2D tensor (time steps × sensor channels) and applies convolutional filters to extract spatial features.

RNN Branch: Processes the same sequential input through a bidirectional LSTM to encode temporal dependencies in system dynamics.

MRAC Compensator: Generates an adaptive correction signal based on the tracking error between the plant output y_p (t) and a stable reference model $y_m(t)$.

The total control command is formulated as:

$$u(t) = u_{nn}(t) + u_{ad}(t) \qquad (1)$$

where u_{nn} denotes the output of the fused deep learning network, and u_{ad} represents the MRAC-derived adaptive action.

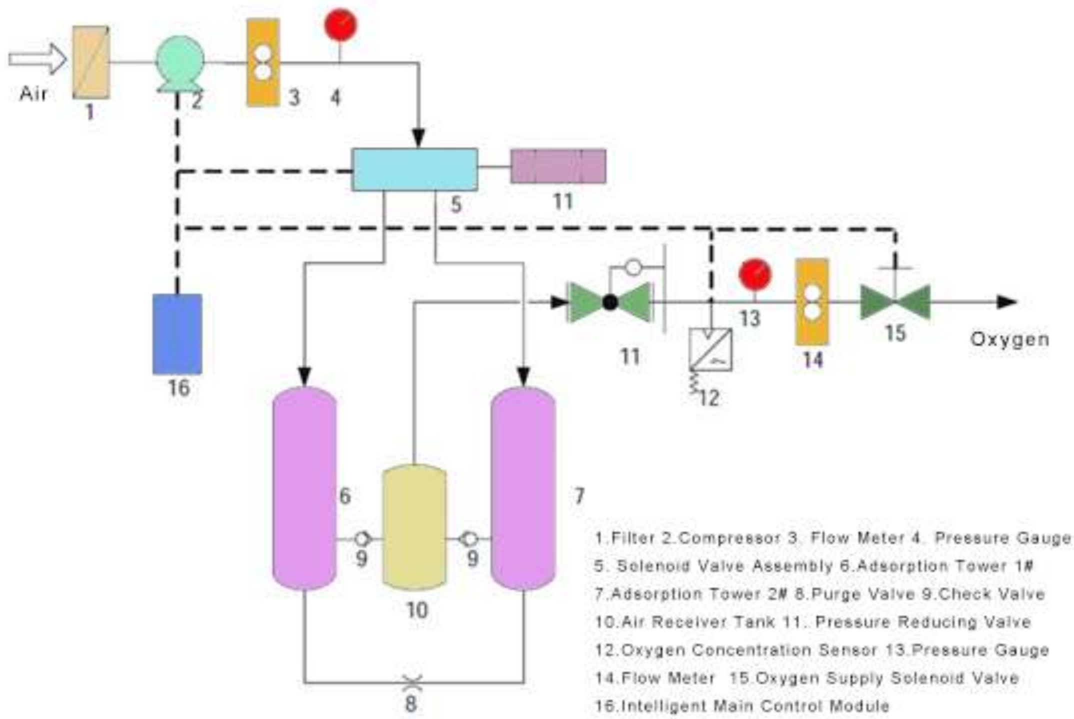

Figure 1 Working Principle of Oxygen Generator

3.2 Feature Extraction and Fusion

Raw signals from five sensors—flow meter, pressure transducer, oxygen concentration sensor, temperature/humidity sensor, and compressor RPM— are z-score normalized and segmented using a sliding window of 64 samples.

- The CNN contains two convolutional layers (32 and 64 filters, kernel size = 3, ReLU activation), followed by max-pooling and flattening.
- The RNN uses a two-layer bidirectional LSTM with 128 hidden units per direction.
- The extracted spatial and temporal features are concatenated and passed through two fully connected layers (128 → 64 neurons) to produce the preliminary control signal u_n.

3.3 MRAC Design and Stability Analysis

An adaptive control system typically includes a reference input, a plant, a controller, and an online adjustment module. During operation, the online adjustment module updates internal controller parameters based on feedback, control inputs, and the reference input to compensate for uncertainties and time-varying behavior, so that the system continues to satisfy performance requirements.

In conventional PID control, the controller parameters are the proportional, integral, and derivative gains. By incorporating adaptive control into the oxygen concentrator, the online adjustment module detects changes in the tracking error and updates controller parameters accordingly, improving adaptability to operating-condition variations. In this work, adaptive control is used to regulate oxygen output flow rate and to adjust the oxygen–air flow ratio for oxygen concentration control, with the goal of meeting target requirements with minimal fluctuation. Parameter optimization via the adaptive module is intended to improve gas-production efficiency and output quality.

The reference model is selected as a first-order system that reflects typical PSA dynamics:

$$G_m(s) = \frac{K_m}{T_m s+1}, \quad K_m = 0.98, \quad T_m = 15s \qquad (2)$$

Let $e(t) = y_p(t) - y_m(t)$ denote the tracking error. The adaptive gains $K_c(t)$ and $K_i(t)$ of a PI-type compensator are updated online according to:

$$\acute{K}_c = -\gamma e(t) r(t) \;,\; \acute{K}_i = -\gamma e(t) \int_0^t e(\tau) d\tau \qquad (3)$$

Where $r(t)$ is the reference input and $\gamma \in [0.05,0.2]$ is the adaptation rate. This update law is derived from the Lyapunov function candidate.

$$\mathrm{V} = \frac{1}{2} e^2 + \frac{1}{2\gamma}(\acute{K}_c^2 + \acute{K}_i^2) \qquad (4)$$

which guarantees boundedness of the tracking error and parameter convergence under standard persistency-of-excitation conditions. The final actuation signal to the solenoid valve and air compressor is computed as:

$$u_{ad}(t) = K_c(t) e(t) + K_i(t) \int_0^t e(\tau) d\tau \qquad (5)$$

3.4 CNN-RNN-MRAC Model

We develop an intelligent control system for oxygen generators that combines a CNN, an RNN, and MRAC to perform real-time adjustments for stable oxygen output under varying workload and environmental conditions. The key idea is to use the CNN to extract cross-sensor spatial features, use the RNN (e.g., LSTM or GRU) to capture temporal dynamics, fuse these features, and then generate control signals with adaptive compensation.

System Implementation Steps:

- Step 1: Data preprocessing: Normalize sensor data (e.g., flow, pressure, temperature, motor speed). To use a CNN, convert the time-series data into a 2D representation by generating spectrograms via short-time Fourier transform (STFT), or by directly forming a matrix using a sliding window (each row is a time step and each column is a sensor channel).
- Step 2: Feature extraction: In the CNN branch, input is 2D data (time steps × number of sensors), treated as a single-channel image or a multi-channel image formed by multiple sensor streams. Convolution and pooling layers extract spatial features. In the RNN branch, input is the original time-series sequence (samples × time steps × features), and LSTM/GRU layers extract temporal features.
- Step 3: Feature fusion: Flatten CNN features and concatenate them with the last-step output of the RNN branch, then feed the fused representation into fully connected layers.
- Step 4: Adaptive control: The adaptive controller receives fused features and the current system state and outputs control variables (e.g., valve opening and motor speed). MRAC adapts controller parameters based on the error between the reference model and the actual output.

Implementation details are shown in Figure 2.

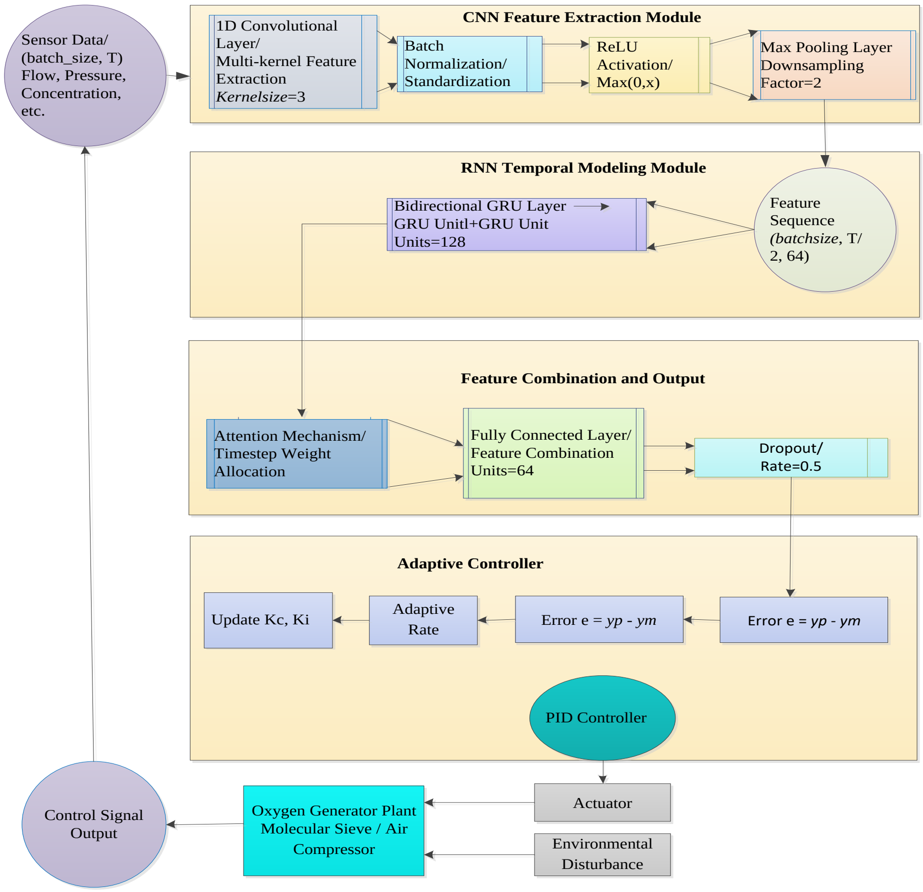

Figure 2 CNN-RNN-MRAC Model

4. Case Study

Experiments were conducted on a comprehensive performance test bench for oxygen concentrators at an electronics company in Anhui Province, China. The oxygen concentrator outlet was connected to the test bench using tubing. The bench includes a paramagnetic oxygen analyzer for real-time oxygen concentration measurement, a thermal mass flow meter for oxygen flow measurement, and a high-precision digital pressure gauge for output pressure monitoring. The data acquisition and processing unit automatically recorded relevant variables, including oxygen concentration, flow rate, pressure, temperature, humidity, current, and power.

To evaluate performance, the proposed CNN–RNN–MRAC controller was compared with a single CNN controller and a traditional PID controller on the same type of oxygen concentrator. The evaluation focused on three signals: oxygen flow rate, oxygen concentration, and output pressure. The oxygen concentrator was tested at three flow-rate setpoints: 1 L/min (low), 3 L/min (medium), and 5 L/min (high). Data samples were collected every 30 minutes over 24 hours (48 time points).

Figures 3–5 show oxygen flow results and errors for the three algorithms. Through corresponding calculations, the PID controller achieved an RMSE of 0.476 with flow control accuracy of ±4%, the single CNN achieved an RMSE of 0.185 with accuracy of ±2.78%, and the proposed CNN–RNN–MRAC achieved an RMSE of 0.107 with accuracy of ±1.3%.

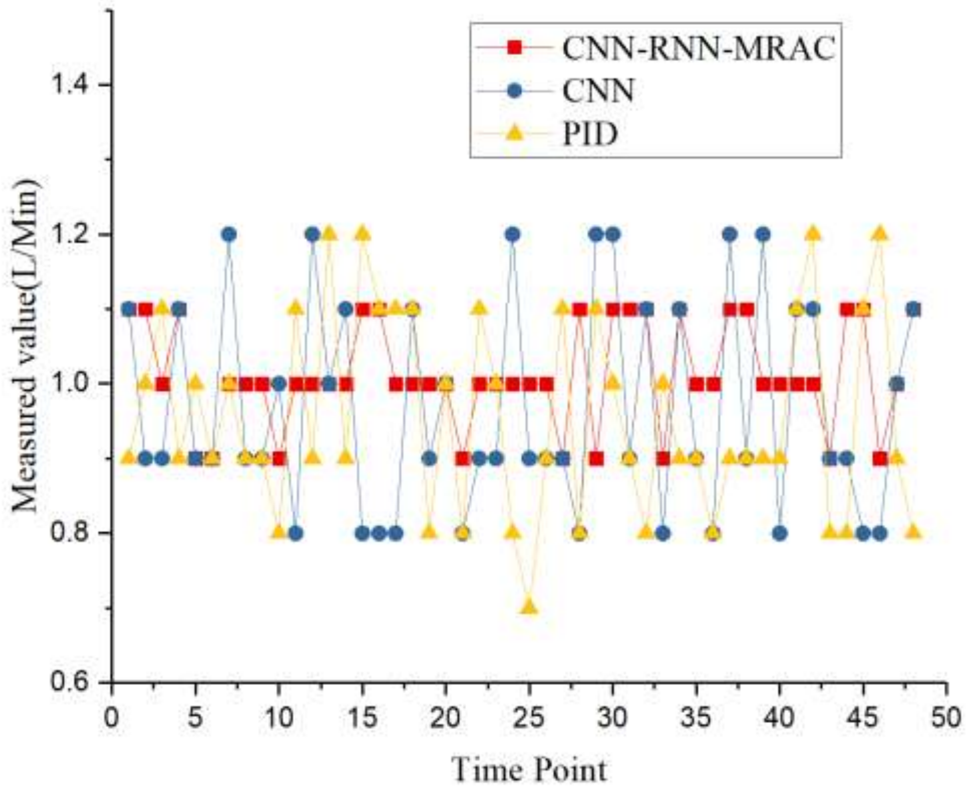

Figure 3 Measured Oxygen Flow Values with Different Algorithms 1 (Set Oxygen Flow = 1 L/Min)

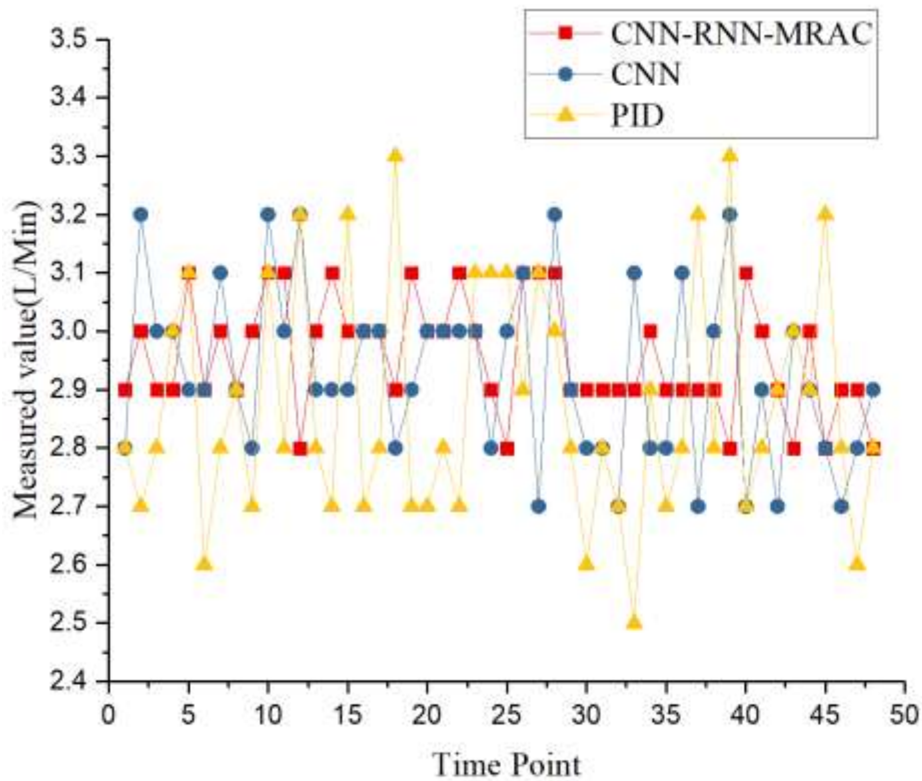

Figure 4 Measured Oxygen Flow Values with Different Algorithms 2 (Set Oxygen Flow = 3 L/Min)

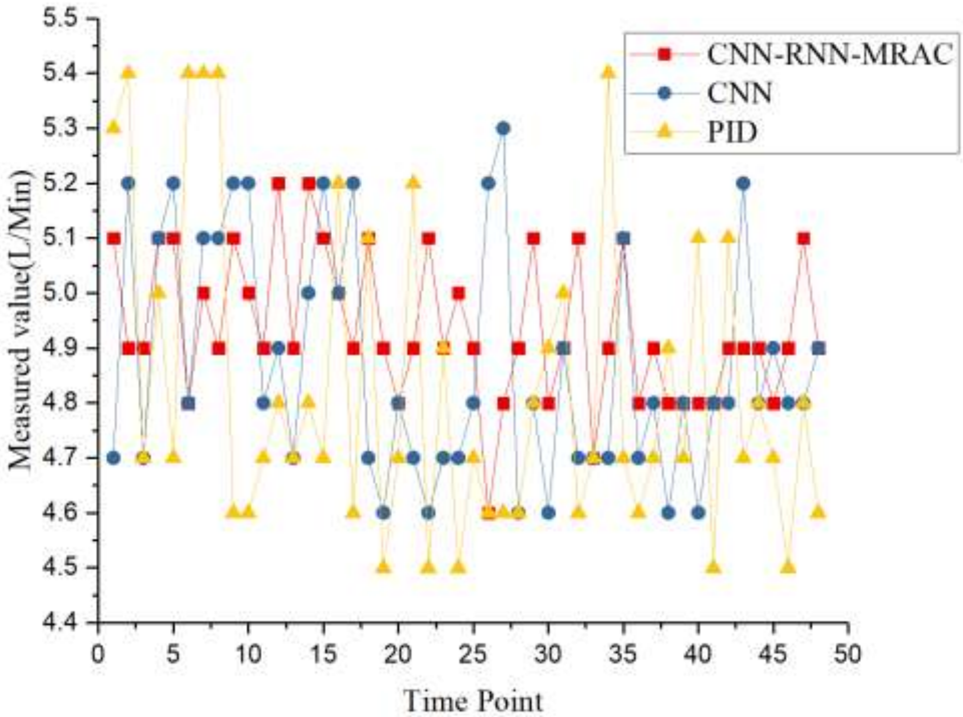

Figure 5 Measured Oxygen Flow Values with Different Algorithms 3 (Set Oxygen Flow =5 L/Min)

The deviations in oxygen concentration monitoring are presented in Figures 6–8. Through corresponding calculations, the PID controller achieved an RMSE of 2.009. The single CNN achieved an RMSE of 1.435 with oxygen concentration control accuracy of ±2%. The proposed CNN–RNN–MRAC achieved an RMSE of 0.858 with oxygen concentration control accuracy of ±1.5%.

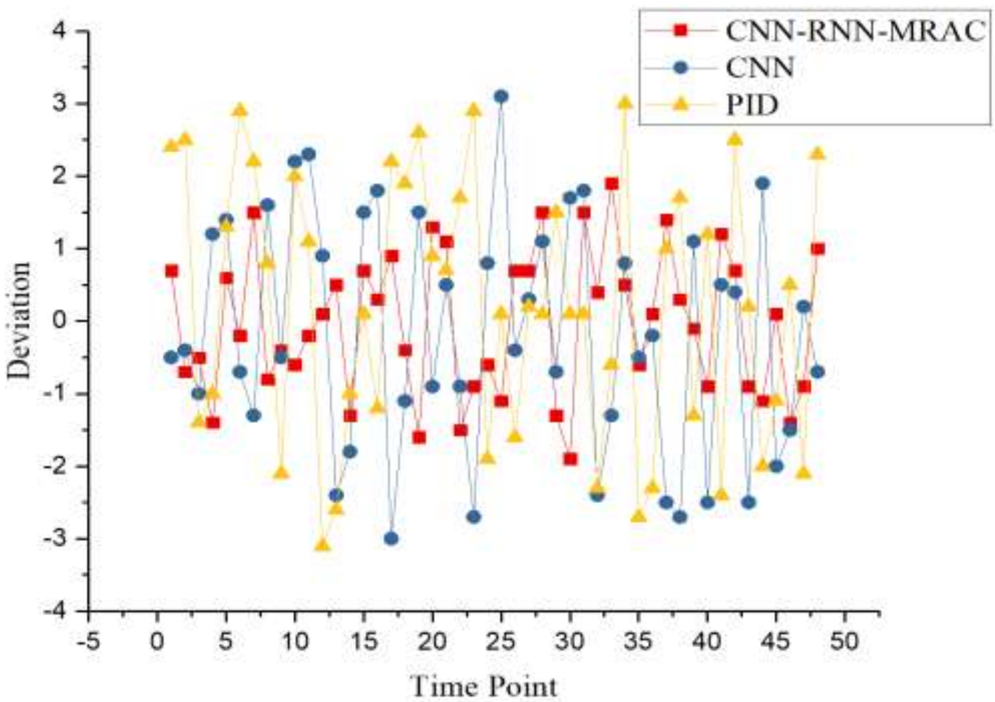

Figure 6 Measured Oxygen Concentration Deviation Values with Different Algorithms 1 (Set Oxygen Flow= 1 L/Min)

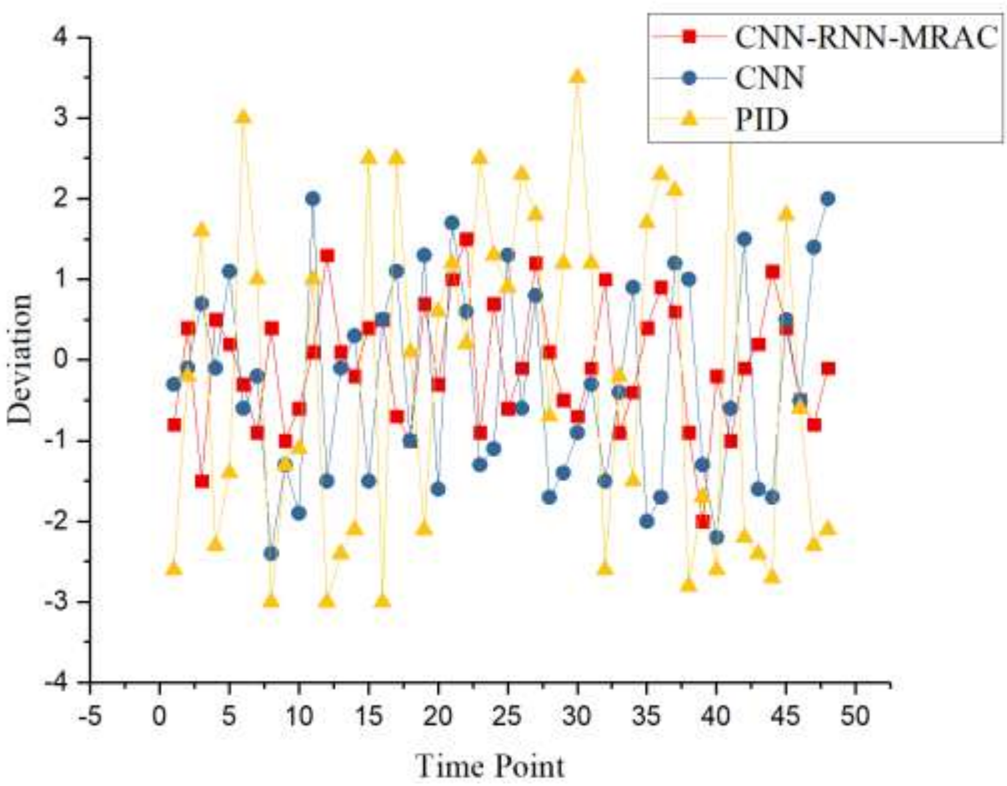

Figure 7 Measured Oxygen Concentration Deviation Values with Different Algorithms 2 (Set Oxygen Flow= 3 L/Min)

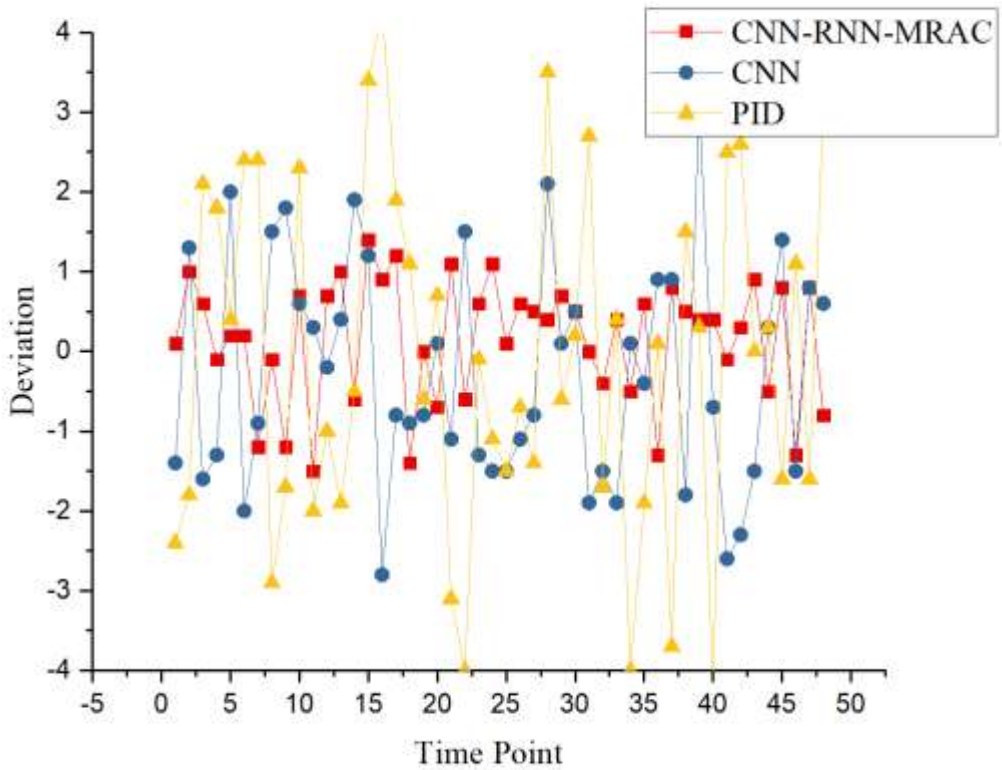

Figure 8 Measured Oxygen Concentration Deviation Values with Different Algorithms 3 (Set Oxygen Flow= 5 L/Min)

Pressure test results are shown in Figures 9–11 for the three algorithms. Through corresponding calculations, the PID controller achieved an RMSE of 5.12 with an average pressure fluctuation rate of 18.47%, the single CNN achieved an RMSE of 4.09 with an average fluctuation rate of 13.68%, and the proposed CNN–RNN–MRAC achieved an RMSE of 2.39 with an average pressure fluctuation rate of 9.75%. Overall, these results suggest that the hybrid CNN–RNN–MRAC model provides improved performance in flow, concentration, and pressure regulation.

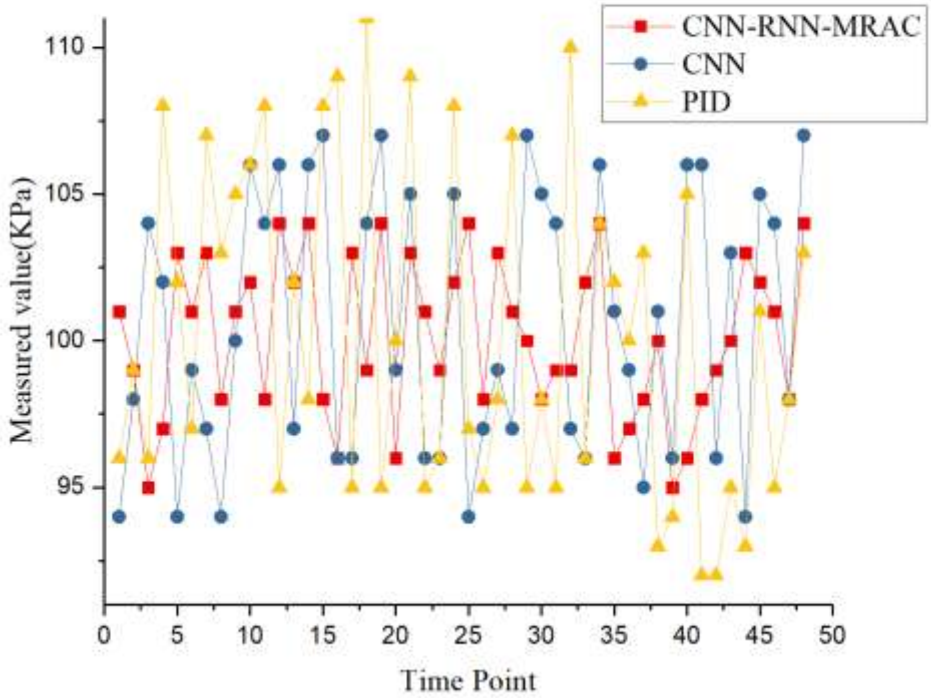

Figure 9 Measured Pressure Values with Different Algorithms 1 (Set Oxygen Flow = 1 /Min)

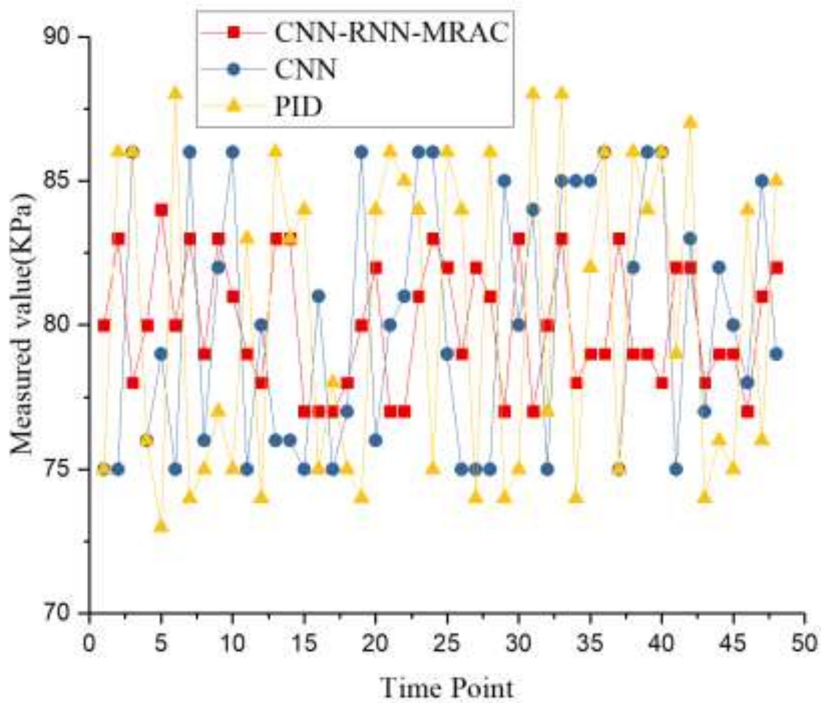

Figure 10 Measured Pressure Values with Different Algorithms 2 (Set Oxygen Flow = 3 /Min)

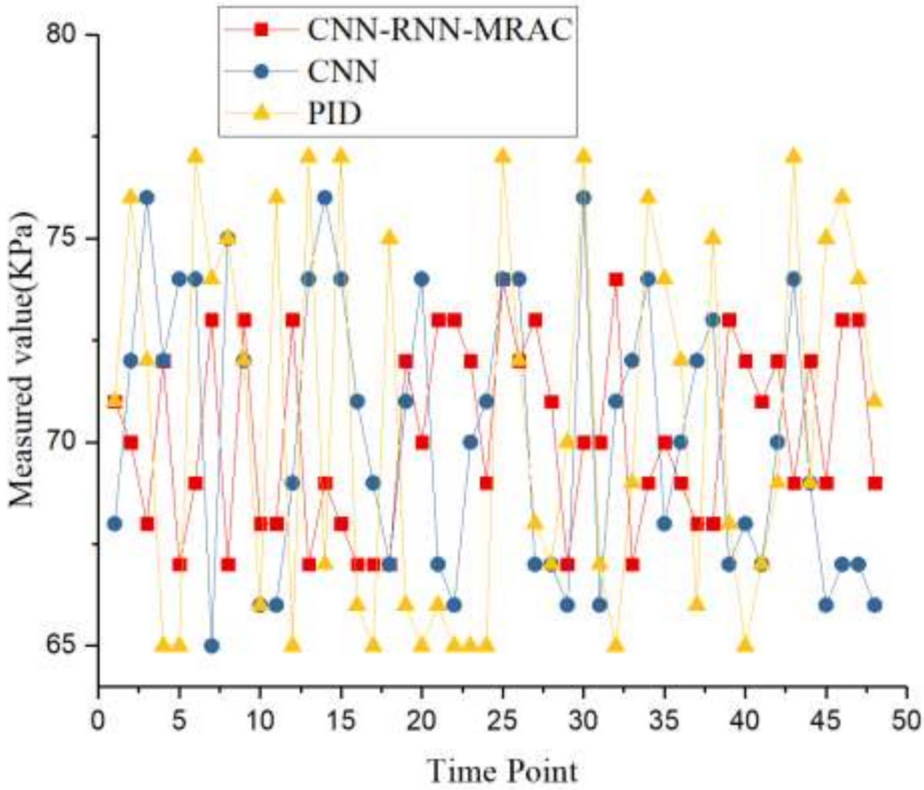

Figure 11 Measured Pressure Values with Different Algorithms 3 (Set Oxygen Flow = 5 /Min)

5. Conclusion

In this research, a hybrid deep-learning control system (CNN–RNN–MRAC) that integrates a CNN, an RNN, and MRAC was designed and applied to commercial oxygen concentrator products tested in Anhui Province, China. Experimental results show that the proposed hybrid approach addresses the nonlinear and time-varying characteristics of the oxygen generation system. By combining CNN/RNN-based feature learning with adaptive control, the method improves control accuracy and stability compared with single-model approaches and traditional PID control, particularly for oxygen concentration, flow, and pressure regulation, enabling high-precision and robust intelligent control of the oxygen generator.

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