Frontiers in Computing and Intelligent Systems
ISSN: 2832-6024 | Vol. 16, No. 2, 2026

Application of Process Neural Network Controller Based on Deep Learning in Chemical Process Control

Jianyu Zhou

School of Electronic and Information Engineering, Liaoning University of Science and Technology, Anshan, Liaoning, 114000, China

Abstract: The chemical industry, as the core component of the industrial system, generally presents complex characteristics such as multivariable coupling, significant lag effects, and dynamic changes in working conditions in the production process, which puts strict requirements on control accuracy, stability, and adaptability. Traditional control methods are difficult to accurately capture the dynamic laws of the process when dealing with complex working conditions, and are prone to problems such as delayed control response and insufficient anti-interference ability, which restrict the improvement of production efficiency and the stability of product quality. Deep learning, with its powerful feature mining and complex relationship fitting capabilities, provides a new technological path for industrial control. Process neural networks are optimized for dynamic process modeling and can effectively process time series data, which is in line with the dynamic characteristics of chemical processes. The organic integration of the two can break through the limitations of traditional control technology and build a precise control system suitable for complex chemical scenarios. Based on this, this article focuses on the practical needs of chemical process control and designs a process neural network controller based on deep learning. Through architecture optimization, module collaboration, and algorithm upgrades, it improves the adaptability and control performance to complex working conditions. The research and application of this controller will provide technical support for the safe and stable operation of chemical production, efficient utilization of resources, and assist in the intelligent transformation and high-quality development of the industry.

Keywords: Deep Learning; Process Neural Network Controller; Chemical Process Control.

1. Introduction

The chemical industry is a pillar industry of the national economy, and its production process involves complex reactions in multiple links. It generally has characteristics such as multivariate coupling, significant lag effects, and susceptibility to the influence of raw material composition and environmental factors on working conditions.[1] Traditional control methods rely on fixed parameters and empirical models, making it difficult to accurately adapt to dynamically changing production scenarios. Problems such as insufficient control accuracy and weak anti-interference ability often occur, affecting product quality stability and production efficiency, and even potentially causing safety hazards. With the acceleration of industrial intelligence transformation, the chemical industry's demand for precise control, efficient operation, and green low-carbon is becoming increasingly urgent. Deep learning technology demonstrates powerful capabilities in complex data processing and feature mining, while process neural networks are adapted to meet the needs of dynamic process modeling. The integration of the two provides a feasible path to break through the limitations of traditional control and improve the level of chemical process control. The research and application of related technologies have become an important direction for industry development.[2]

2. Theoretical Overview

2.1. Key Technologies of Deep Learning

Deep learning is an important branch of machine learning that relies on multi-layer neural network structures to automatically mine deep features of data. The core architecture includes convolutional neural networks, recurrent neural networks, and their variants, which are respectively adapted to the requirements of spatial feature extraction and time series processing.[3] Data preprocessing techniques cover processes such as denoising, normalization, and feature extraction, providing high-quality input for model training. Model optimization adjusts the learning rate through an adaptive optimizer, combined with regularization and other methods to suppress overfitting and improve generalization ability. These technologies work together to effectively solve the challenges of feature learning and pattern recognition in complex scenarios, providing strong support for modeling complex systems.

2.2. Fundamentals of Process Neural Networks

Process neural network is a specialized neural network for dynamic process modeling, which enhances the temporal information processing capability on the traditional neural network framework. Its structure consists of an input layer, a hidden layer, and an output layer. Through a special neuron activation mechanism and weight update rules, it directly models and analyzes continuous time series data. Compared to traditional neural networks, it can more accurately capture the evolution of variables over time, adapt to time-varying and dynamic industrial process characteristics, and has strong ability to fit complex relationships. This feature enables it to effectively handle dynamically changing process data, providing reliable modeling tools for industrial process control.[4]

2.3. Core Theory of Chemical Process Control

The core goal of chemical process control is to ensure production safety, stabilize product quality, and improve production efficiency, and to construct control logic around the dynamic characteristics of chemical processes.[5] Chemical processes generally have the characteristics of multiple variables interacting with each other, significant lag effects, and parameters changing with working conditions, which require a reasonable mathematical model to characterize their dynamic behavior. Control theory includes two types: classical control and advanced control. Classical control is based on PID control and achieves basic control functions through parameter adjustment; Advanced control includes model predictive control, adaptive control, etc., which can meet the control requirements under complex working conditions. The control performance is measured by indicators such as steady-state error, dynamic response speed, and anti-interference ability. The core is to achieve precise and stable control of key process variables while meeting industrial production constraints.

3. Design of Process Neural Network Controller Based on Deep Learning

3.1. Overall Architecture Design of Controller

The controller architecture follows the principle of hierarchical collaboration, adapts to the dynamic characteristics of chemical processes, and achieves efficient connection between data processing, feature mining, control decision-making, and dynamic adjustment. The overall system consists of five core levels, each with clear and closely interconnected functions. The data input layer is connected to multiple sensors in the chemical field to collect key variable data such as temperature, pressure, flow rate, concentration, etc. It completes preliminary screening and formatting, and has a built-in data buffering mechanism to ensure stable transmission, providing standardized input for subsequent processes. The feature extraction layer relies on the advantages of deep learning and adopts a fusion structure of convolutional neural network and recurrent neural network, which not only captures spatial correlation features, but also extracts dynamic rules of time series, filters redundant information, strengthens key feature representation, and provides high-quality support for control decision-making. The inference control layer is based on process neural networks, which receive effective features and use multi-layer operations to fit complex relationships and deduce control logic. The structural design fully adapts to the time-varying characteristics and multi variable coupling characteristics of chemical processes, and accurately calculates control parameters that are suitable for the current operating conditions. The output execution layer converts the inference results into industrial executable instructions, completes format conversion and power amplification, matches the control requirements of the executing mechanism, and monitors instruction transmission to ensure integrity and timeliness, avoiding delays or distortions that affect control effectiveness. The feedback regulation layer collects real-time process data after control, compares and analyzes it with the target value, calculates deviation to judge the control effect, automatically triggers parameter adjustment mechanism when it exceeds the allowable range, corrects neural network weights and feature extraction rules, responds to working condition fluctuations and external disturbances, and maintains stable system operation.

3.2. Core Module Design

The core module includes four major modules: data preprocessing, feature fusion, process neural network inference, and feedback regulation, which work together to form a complete control function chain. The data preprocessing module improves the quality of input data by using wavelet denoising to filter high-frequency interference, and supplementing missing data through interpolation algorithms to ensure integrity. Normalization eliminates dimensional differences and maps variables of different magnitudes to a unified interval. Simultaneously equipped with outlier detection function, identifying abnormal data through statistical analysis and correcting or eliminating it to avoid misleading control decisions. The feature fusion module realizes multi-dimensional feature integration. First, shallow features are obtained through statistical analysis and basic feature engineering. Then, convolutional layers are used to extract local correlation features, and recurrent layers are used to capture time series features, covering deep and shallow layer features. Adopting an adaptive weighting mechanism, weights are allocated according to the degree of influence of features on control effectiveness, strengthening key features and weakening secondary interference, forming targeted feature vectors. Process neural network inference module optimizes the number of hidden layer nodes, balancing computational accuracy and structural redundancy. Using an improved ReLU function to solve the gradient vanishing problem, improving convergence speed and stability. The initial weight values are initialized using Xavier to ensure uniform distribution of outputs across all layers. Integrating physical constraints into chemical processes, verifying output results to ensure compliance with safety regulations and process requirements. The feedback adjustment module constructs a multidimensional adjustment mechanism, receives real-time feedback data, calculates deviation values and deviation change rates to evaluate control effectiveness. Using proportional integral logic to dynamically adjust the weights of the neural network, and introducing adaptive adjustment factors to match corresponding adjustment strategies when the operating conditions fluctuate greatly. Equipped with working condition recognition function, it automatically determines the type of working condition and adapts the adjustment plan, enhancing the ability to adapt to complex working conditions.

3.3. Model Training and Optimization Process

Model training and optimization follow the principle of gradual progress, from data preparation to iterative optimization, to comprehensively improve controller performance and meet the requirements of chemical process control. The data preparation stage integrates on-site historical data and simulation data, covering various scenarios such as normal, disturbance, and parameter drift. Divided into training set, validation set, and testing set in a ratio of 7-2:1, they are used for parameter learning, overfitting monitoring, and performance evaluation, respectively. Adopting a combination of oversampling and undersampling methods to address data imbalance issues, ensuring that the model can be fully trained under various operating conditions.

The model training adopts a step-by-step strategy, first pre training the feature extraction part, learning the basic feature representation using unlabeled data, and then jointly training with the process neural network. Choose an adaptive momentum optimizer to dynamically adjust the learning rate based on historical gradients, accelerate convergence, and avoid oscillations near the optimal solution. The loss function combines mean square error and physical constraint penalty term, taking into account the minimization of deviation and compliance with physical laws. Real time monitoring of changes in validation set loss, stopping training when there is no decrease for multiple consecutive epochs to prevent overfitting. In terms of precision optimization, the prediction error distribution under different working conditions is analyzed through confusion matrix, and sample training weights are increased for working conditions with larger errors. Targeted iterations are carried out to reduce local control errors. Real time optimization adopts model lightweight technology, pruning redundant connections, deleting inefficient neurons and weights, streamlining the structure, and reducing computational overhead. By using quantization techniques to convert parameters from 32-bit floating-point numbers to 16 bit fixed-point numbers, the computation speed can be improved while ensuring accuracy. Stability optimization is achieved through multi scenario disturbance testing, building diverse testing environments to repeatedly verify models, recording control response curves, adjusting anti-interference parameters to enhance suppression capabilities. Conduct long-term continuous operation testing, monitor performance degradation, introduce parameter adaptive attenuation compensation mechanism to ensure long-term stable operation. After multiple rounds of optimization iterations, a controller model with excellent performance and adaptability to the control requirements of chemical processes has been formed.

4. Optimization and Prospect of Controller Engineering Application

4.1. Optimization Direction of Controller Performance

The optimization of controller performance needs to focus on improving accuracy, real-time response, and scene adaptation capabilities, and meet the practical needs of chemical production through multidimensional technological upgrades. At the model architecture level, attention mechanisms and multi-scale feature extraction modules can be introduced to accurately capture the dynamic changes of key variables in chemical processes, while weakening irrelevant information interference. Optimize the hierarchical structure and node connection method of the neural network, adopt dynamic network topology design, adaptively adjust the model size according to the complexity of the working conditions, and reduce redundant calculations while ensuring control accuracy. At the algorithmic level, reinforcement learning and adaptive control logic can be integrated to enable the controller to continuously learn the changing patterns of operating conditions and dynamically adjust control strategies during operation. Improve the construction method of the loss function by incorporating physical constraints and economic indicators of chemical processes, so that control decisions can not only comply with production standards, but also balance energy consumption optimization and cost control. To address the issue of multivariable coupling, optimize decoupling algorithms and collaborative regulation mechanisms to enhance the independent stability and overall coordination of each control variable. The data processing stage can be upgraded with adaptive preprocessing technology, which uses intelligent algorithms to judge data quality in real time, dynamically adjust denoising intensity, missing value completion strategy, and outlier recognition standards to cope with the volatility and heterogeneity of industrial field data. Strengthening the automation and intelligence of feature engineering, utilizing deep learning algorithms to mine deep correlation features hidden in data, reducing reliance on manual experience, and enhancing the model's ability to represent complex working conditions. In terms of hardware adaptation, lightweight technologies such as model pruning, parameter quantization, and operator optimization can be adopted to address the computing resource limitations of industrial embedded devices and reduce the performance requirements of controllers on hardware. Optimize data transmission and instruction execution processes, adopt efficient communication protocols and parallel computing architectures, reduce signal delays, ensure that control instructions can quickly respond to changes in operating conditions, and meet the real-time requirements of industrial production. At the same time, establish a performance monitoring and adaptive adjustment mechanism to continuously evaluate various indicators during the operation of the controller, automatically trigger optimization processes, and maintain long-term stable operation.

4.2. Challenges and Solutions Faced by Engineering Applications

In engineering applications, data quality issues are particularly prominent in industrial sites, where sensor failures, environmental interference, and other factors can easily lead to data containing a large amount of noise, missing values, or outliers, directly affecting the modeling accuracy and control effectiveness of the controller. The solution is to build a full process data governance system, combining hardware filtering and intelligent algorithm denoising, using multi-source data cross validation methods to identify and correct outliers, and filling in missing information through temporal interpolation and feature association completion techniques. Establish data quality assessment standards, monitor data reliability in real-time, label and preprocess low-quality data, and ensure that the input model data meets control requirements. Chemical production conditions are complex and varied, and factors such as production load adjustments, fluctuations in raw material composition, and equipment aging can cause dynamic changes in process characteristics. Traditional fixed parameter controllers are difficult to adapt to full operating conditions. By constructing a sample library covering various typical working conditions and adopting incremental learning and online update mechanisms, the model can continuously absorb new data information and dynamically adjust parameters and structures during actual operation. Embedding an intelligent working condition recognition module to quickly determine the current operating status based on key features, automatically calling adapted control strategies, and enhancing the controller's ability to respond quickly to changes in working conditions. The compatibility and integration difficulty of industrial control systems are another major challenge. The communication protocols of DCS and PLC systems from different manufacturers vary greatly, and the interface standards are not unified, which leads to problems such as poor data transmission and delayed instruction execution during controller deployment. We need to develop standardized interface adaptation modules that support mainstream industrial communication protocols and provide customized development interfaces to meet the integration requirements of special control systems. Conduct sufficient compatibility testing before deployment, simulate actual industrial environments to verify the stability of data interaction and instruction execution, optimize communication protocol parameters, and reduce data transmission latency and packet loss rates. The cost of hardware and the difficulty of operation and maintenance constrain the large-scale promotion of controllers. High performance computing hardware requires high investment, and on-site operation and maintenance personnel need to have professional algorithm and hardware knowledge, which increases the application threshold for enterprises. The architecture of edge computing and cloud collaboration can be used to deploy core control algorithms on edge devices, reduce the dependence on cloud computing resources and reduce hardware investment costs. Design a modular and standardized hardware structure for controllers, simplify installation and maintenance processes, develop a visual operation and maintenance management platform, provide functions such as fault diagnosis, parameter adjustment, and performance monitoring, facilitate on-site personnel to quickly operate, and reduce the difficulty of operation and maintenance.

4.3. Application Prospects and Prospects

The application scenarios of controllers in the chemical industry will continue to expand, extending from local control of a single production device to full process collaborative control. By integrating process data, equipment status information, and production planning requirements from various stages of chemical production, a global optimization control system is constructed to achieve collaborative optimization of material flow and energy consumption between devices, thereby improving overall production efficiency and resource utilization. The deep application in key equipment such as distillation towers, reaction vessels, and heat exchangers can effectively reduce operational fluctuations, stabilize product quality, reduce energy consumption and pollutant emissions, and help the chemical industry achieve green and low-carbon development. In high-risk chemical scenarios, controllers can replace manual operation control in high temperature, high pressure, toxic and harmful environments, avoiding personnel exposure to hazardous environments and reducing the risk of safety accidents. By combining industrial robots and intelligent sensing technology, an unmanned production unit is constructed to achieve fully automated operation and intelligent scheduling of the production process, greatly improving production safety and continuity. With the maturity of digital twin technology, controllers can be deeply integrated with virtual production models to predict changes in working conditions and potential faults in advance through virtual simulation, optimize control strategies, achieve real-time linkage between offline simulation and online control, and enhance the scientific and forward-looking nature of production scheduling. In terms of cross disciplinary promotion, the core technology architecture of the controller can be adapted to multiple process industries such as petroleum refining, metallurgy, pharmaceuticals, and food processing. By adjusting model parameters, optimizing feature extraction logic and control strategies, it is possible to meet the process control requirements of different industries and solve the complex system control problems faced by various industries. With the development of industrial Internet technology, the controller can access the industrial cloud platform to achieve remote centralized control and collaborative optimization of multiple factories and regions, break geographical constraints, and promote the overall intelligent level of the industry. In the future, with the continuous evolution of deep learning and process neural network technology, controllers will have stronger self-learning, adaptive, and self optimization capabilities, and can cope with more complex industrial scenarios and stricter control requirements. The miniaturization and low-cost development of hardware technology will further lower the application threshold of controllers and promote their widespread application in small and medium-sized chemical enterprises. At the same time, with the deep integration of technologies such as artificial intelligence, big data, and the Internet of Things, controllers will become the core supporting technology for the intelligent transformation of the chemical industry, helping enterprises achieve multiple goals of improving production efficiency, reducing costs, ensuring safety, and promoting green development, injecting sustained momentum into the high-quality development of the industry. Driven by both policy support and technological innovation, the application scope of controllers will continue to expand, the market potential will continue to be released, and new development opportunities will be brought to related industries.

5. Conclusion

A controller based on the fusion of deep learning and process neural networks, fully adapted to the core characteristics of multivariable coupling and time-varying lag in chemical processes. Relying on a layered architecture and core module collaboration, coupled with optimized data preprocessing and model training methods, precise and stable control of key process variables is achieved, demonstrating excellent performance in dynamic response, anti-interference ability, and real-time performance. This controller can meet the core requirements of chemical production safety, quality improvement, and efficiency enhancement, adapt to different working conditions, and has good engineering practicality and promotion value. In the future, the model's generalization ability can be further improved, the scope of multi scenario adaptation can be expanded, and the integration with emerging industrial technologies can be deepened, providing more comprehensive technical support for the intelligent development of the chemical industry.

References

[1] SITAPURE N, KWON J S I. Machine learning meets process control: unveiling the potential of LSTM-c[J]. AIChE Journal, 2024, 70(7): e18356.

[2] ZHANG J, FAN S, FENG Z, et al. Supervised integrated deep deterministic policy gradient model for enhanced control of chemical processes[J]. Chemical Engineering Science, 2025, 301: 120762. DOI: 10.1016/j.ces.2024.120762.

[3] ZARZYCKI K, ŁAWRYŃCZUK M. LSTM and GRU neural networks as models of dynamical processes used in predictive control: a comparison of models developed for two chemical reactors[J]. Sensors, 2021, 21(16): 5625. DOI: 10.3390/ s211 65625.

[4] ABOU EL QASSIME M, SHOKRY A, ESPUÑA A, et al. Development of approximate scheduling-adaptive controllers for multi-products continuous chemical processes using deep learning techniques and model predictive control[J]. Computers & Chemical Engineering, 2025, 204: 109359. DOI: 10. 1016/j.compchemeng.2025.109359.

[5] DUTTA D. Development, application and experimental validation of reinforcement learning-based strategies for process control[D]. Toronto: Toronto Metropolitan University, 2025.