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Comparative analysis of neural network architectures for adaptive control of nonlinear thermal systems

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Abstract: This paper presents a comparative study of control strategies for nonlinear thermal systems with significant time delay and thermal inertia. Three controllers are evaluated: a classical PID controller, a multilayer perceptron (MLP)-based adaptive controller, and a recurrent neural network controller based on a gated recurrent unit (GRU). A nonlinear thermal process model is used as a benchmark, incorporating heat transfer dynamics, radiative losses, actuator saturation, and external disturbances. The controllers are assessed based on temperature tracking performance, tracking error, control signal behavior, and mean squared error (MSE). The results demonstrate that neural network-based controllers outperform the classical PID approach. The MLP-based controller improves transient response and reduces tracking error. The GRU-based controller further enhances performance by capturing temporal dependencies, leading to improved tracking accuracy and disturbance rejection.

However, the improved performance of the GRU controller is accompanied by increased variability in the control signal, highlighting a trade-off between accuracy and smoothness. The findings confirm the potential of recurrent neural networks for adaptive control of nonlinear and delay-dominant thermal processes.

Keywords: adaptive control, thermal systems, annealing furnace, neural networks, GRU, MLP, PID control, nonlinear systems, time delay, temperature regulation

1. Introduction

Temperature control is a key problem in industrial automation, as thermal trajectories directly affect product quality, energy efficiency, and process stability. In systems such as continuous annealing and slab reheating furnaces, the controller must achieve target temperatures while avoiding overheating, energy losses, and operational constraints. Due to these requirements, temperature control remains a central topic in advanced process control [1].

Industrial thermal systems are characterized by several fundamental properties. First, thermal inertia leads to slow system response due to energy accumulation in both the material and furnace structure. Second, nonlinear radiative heat transfer introduces operating-point-dependent dynamics, as radiative losses scale with the fourth power of temperature [2]. Third, time delays arise from actuator dynamics, transport effects, and thermal propagation. Finally, disturbances such as load variations and power limitations further complicate control design. These characteristics are inherent to the process and cannot be neglected [3].

As a result, controllers tuned for one operating condition may perform poorly under others. Although PID controllers remain widely used due to their simplicity and robustness, their performance degrades in nonlinear and delay-dominant systems. In practice, PID tuning is often heuristic and may lead to suboptimal behavior, particularly during transients and disturbance rejection [4].

To address these limitations, adaptive and learning-based control approaches have been extensively explored. Neural networks are especially attractive due to their ability to approximate nonlinear relationships without requiring an exact analytical model. However, the key question is which neural architecture is better suited for systems with delay and nonlinear dynamics. This study addresses this issue by comparing feedforward (MLP) and recurrent (GRU) neural controllers under a unified thermal benchmark, with assumptions explicitly stated where model details are not fully defined [5].

Related work

Classical PID design for industrial systems is strongly rooted in low-order models with time delay. Internal model control (IMC)-based approaches provide systematic tuning rules based on first-order-plus-dead-time approximations, enabling practical and robust controller design [6]. These methods remain relevant for thermal systems due to their transparency and ease of implementation.

However, furnace-specific studies highlight the limitations of fixed-gain control. Due to strong inertia, nonlinear heat transfer, and process constraints, model-based approaches such as nonlinear model predictive control (MPC) often provide improved performance, particularly in terms of energy efficiency and disturbance rejection [7], [8].

Neural network-based control methods offer an alternative by capturing nonlinear system behavior. Feedforward networks such as multilayer perceptrons (MLP) can approximate static nonlinear mappings, making them suitable for control correction tasks. However, they do not explicitly account for temporal dependencies in system dynamics.

Intelligent control strategies for nonlinear dynamic systems, including adaptive and neural network-based approaches, have been actively developed in [15], [16].

Recurrent neural networks (RNNs) address this limitation by incorporating memory of past states. Early work by Elman introduced recurrent structures capable of representing temporal patterns [9], while later architectures such as LSTM and GRU improved learning of long-term dependencies through gating mechanisms. Empirical studies

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show that GRU networks can achieve performance comparable to LSTM with lower computational complexity.

In the context of thermal systems, temporal dependencies are critical due to inherent delays and slow dynamics. Recent studies on annealing furnaces demonstrate that recurrent neural models can improve control performance by capturing these effects more effectively [10]. However, direct comparisons between feedforward and recurrent neural controllers under identical nonlinear thermal conditions remain limited, which motivates the present study.

2. Research methodology

The benchmark in this article represents a single-zone lumped thermal process intended to mimic the dominant dynamics of an industrial heating section rather than reproduce a specific commercial furnace in full geometric detail. This is an explicit assumption. Since plant-identified parameters are not available, representative simulation parameters are assumed and explicitly reported. Another explicit assumption is that the neural controllers are trained offline on simulated episodes and then frozen for deployment. No online weight adaptation, Lyapunov update law, or reinforcement-learning exploration is assumed.

The continuous-time plant model is derived from a heat balance with bounded heating power, linearized convective loss, and radiative loss:

$$C_{th}\frac{dT(t)}{dt} = \alpha_P(t)\,\eta P_{max}u(t-\tau) - h(T(t)-T_a) - \varepsilon\sigma A\left[(T(t)+273.15)^4 - (T_a + 273.15)^4\right] + d(t).$$

Here, $T(t)$ is process temperature in $^\circ C$, $u(t) \in [0,1]$ is normalized heater demand, C_{th} is effective thermal capacitance in J/K, P_{max} is maximum heater power in W, η is heater-to-process efficiency, h is the linear heat-loss coefficient in W/K, ε is effective emissivity, A is effective radiating area in m^2, $\sigma = 5.67 \times 10^{-8}\, W\,m^{-2}\,K^{-4}$ is the Stefan–Boltzmann constant, τ is input delay in seconds, T_a is ambient temperature, $\alpha_P(t) \in (0,1]$ models temporary power-availability reduction, and $d(t)$ is an additive disturbance heat flow in watts. The use of radiative terms in furnace modeling is standard in control-oriented furnace literature, and the T^4 dependence follows directly from the Stefan–Boltzmann law [11].

The assumed numerical values are chosen to represent a medium-scale industrial heating section:

The parameters of the thermal process model used in the simulations are summarized in Table 1.

Table 1

Parameters of the thermal process model used in simulations

Parameter	Meaning	Assumed value	Units
C_{th}	Effective thermal capacitance	8.0×10^4	J/K
P_{max}	Maximum heater power	3.5×10^5	W
η	Heater efficiency	0.82	–
h	Linear heat-loss coefficient	75	W/K
ε	Effective emissivity	0.75	–
A	Effective radiating area	5.5	m^2
τ	Input delay	28	s
T_a	Ambient temperature	25	$^\circ$C

These assumed values imply strong operating-point dependence. Linearizing the radiative term around $T^\star$ yields an effective loss coefficient

$$h_{eff}(T^\star) = h + 4\varepsilon\sigma A(T^\star + 273.15)^3.$$

For the assumed benchmark, $h_{eff} \approx 355\ W/K$ near $350^\circ C$ and $h_{eff} \approx 865\ W/K$ near $650^\circ C$, so the apparent local time constant C_{th}/h_{eff} changes from about $135\ s$ to $55\ s$. This single calculation already explains why fixed gains are unlikely to remain uniformly optimal.

The discrete-time simulator uses forward Euler integration with $\Delta t = 1\ s$, giving

$$T_{k+1} = T_k + \frac{\Delta t}{C_{th}}\left[\alpha_{P,k}\eta P_{max}u_{k-n_\tau} - h(T_k - T_a) - \varepsilon\sigma A\left((T_k + 273.15)^4 - (T_a + 273.15)^4\right) + d_k\right],$$

with delay $n_\tau = \tau/\Delta t = 28$ implemented as a FIFO buffer.

The baseline controller is a PID law with anti-windup:

$$u_{k,raw} = K_c\left(e_k + \frac{\Delta t}{\tau_I}\sum_{i=0}^{k} e_i + \tau_D\frac{e_k - e_{k-1}}{\Delta t}\right), \qquad u_k = sat_{[0,1]}(u_{k,raw}),$$

$$I_{k+1} = I_k + \Delta t\, e_k + \frac{\Delta t}{T_t}(u_k - u_{k,raw}).$$

The tuning rationale follows IMC/FOPDT practice. Linearizing the nonlinear plant around $500^\circ C$ gives an approximate first-order-plus-dead-time model with steady-state gain $K \approx 328\ ^\circ C/p.u.$, dominant time constant $\tau_p \approx 85\ s$, and delay $\theta = 28\ s$. Using a conservative IMC-style choice $\lambda = 45\ s$ gives $K_c \approx \tau_p/[K(\lambda + \theta)] \approx 3.6 \times 10^{-3}\ ^\circ C^{-1}$, which is the value used here; $\tau_I = 130\ s$ and $\tau_D = 18\ s$ are then selected by modest detuning for better robustness under saturation and radiative nonlinearity. This is an assumed but analytically motivated tuning, not a plant-certified industrial setting.

The MLP-based adaptive controller augments the PID output with a nonlinear state-dependent correction:

$$u_k = sat_{[0,1]}(u_k^{PID} + \Delta u_k^{MLP}), \qquad \Delta u_k^{MLP} = clip(f_\theta(x_k), -0.25, 0.25).$$

The regressor is

$$x_k = [e_k, e_{k-1}, I_k, T_k, r_k, u_{k-1}, \alpha_{P,k}]^\top.$$

The assumed architecture is a two-hidden-layer MLP with widths 32 and 16, hyperbolic tangent activations, and a scalar linear output. This controller remains memoryless in the strict state-space sense, but the regressor includes limited dynamic context through lagged error and previous control. The theoretical justification is straightforward: an MLP can approximate nonlinear static maps, and earlier neural-control work established the viability of embedding such maps in nonlinear control structures [12].

The RNN-based adaptive controller uses a GRU cell:

$$u_k = sat_{[0,1]}(u_k^{PID} + \Delta u_k^{GRU}), \qquad \Delta u_k^{GRU} = clip(W_o h_k + b_o, -0.25, 0.25),$$

with recurrent state

$$z_k = \sigma(W_z x_k + U_z h_{k-1} + b_z), \qquad q_k = \sigma(W_q x_k + U_q h_{k-1} + b_q),$$

$$\tilde{h}_k = tanh(W_h x_k + U_h(q_k \odot h_{k-1}) + b_h), \qquad h_k = (1 - z_k) \odot h_{k-1} + z_k \odot \tilde{h}_k.$$

A hidden dimension of 16 is assumed. GRU is chosen rather than plain RNN because gated recurrence is substantially better suited to long-lag temporal dependencies, and rather than full LSTM because GRU offers a more compact recurrent law while retaining strong temporal modeling performance. This choice is directly consistent with the recurrent-network literature and with recent annealing-furnace work using LSTM-family models for long thermal time series [13].

The neural controllers are trained offline on 3000 randomized simulated episodes. This figure is assumed because the training dataset is generated using simulated scenarios. Each episode samples parameter perturbations of $\pm 15\%$ on C_{th}, h, η, and τ; setpoints are drawn as piecewise-constant trajectories in the range $250\text{–}700^\circ C$; disturbances include additive heat-sink pulses and power-availability drops. The cost function is

$$J = \frac{1}{N}\sum_{k=1}^{N} e_k^2 + \lambda_{\Delta u}\frac{1}{N}\sum_{k=1}^{N}(u_k - u_{k-1})^2 + \lambda_{ov}\frac{1}{N}\sum_{k=1}^{N} max(0, T_k - r_k)^2,$$

with assumed weights $\lambda_{\Delta u} = 0.02$ and $\lambda_{ov} = 0.5$. Adam with learning rate 10^{-3}, batch size 64, and early stopping is assumed for both networks; GRU training uses truncated backpropagation through time over windows of 40 samples.

Performance is evaluated using settling time t_s to the 2% band, overshoot M_p, mean squared error,

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(r_k - T_k)^2,$$

disturbance-recovery time, and practical BIBO stability. Disturbance-recovery time is defined as the time from the end of a disturbance interval until the output re-enters the 2% band and remains there for at least $20\,s$. Practical stability is interpreted conservatively: for bounded reference profiles, bounded disturbances, and actuator saturation, the temperature and actuator commands must remain bounded in all test scenarios [14].

The benchmark experiment uses $\Delta t = 1\,s$, horizon $1200\,s$, initial temperature $T(0) = 300^\circ C$, and the following setpoint profile:

$$r(t) = 350^\circ C,\ 0 \le t < 300\,s; \qquad r(t) = 650^\circ C,\ 300 \le t \le 1200\,s.$$

Two disturbances are imposed during the final setpoint segment: a load-insertion heat sink $d(t) = -10\,kW$ for $520 \le t < 620\,s$, and a temporary power-availability limitation $\alpha_P(t) = 0.80$ for $760 \le t < 860\,s$. Saturation $0 \le u \le 1$ is active for all controllers, and no measurement noise is added because sensor characteristics are not explicitly defined in the model.

3. Results and discussion

Temperature Response

The temperature response of the system under different control strategies is shown in Fig. 1.

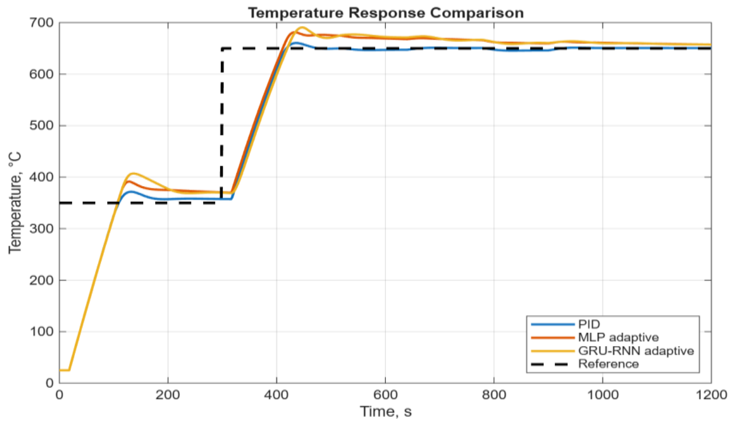

Fig. 1. Temperature response of the system under PID, MLP-based, and GRU-based control strategies

All controllers successfully track the reference signal, including the step increase from 350 °C to 650 °C. However, clear differences can be observed in transient performance.

The PID controller exhibits the slowest response and the largest deviation from the reference during both heating stages. The MLP-based controller improves the transient behavior by reducing overshoot and accelerating convergence.

The GRU-based controller demonstrates the most balanced response, achieving fast convergence while maintaining relatively low overshoot. This behavior indicates that the recurrent structure is more effective in handling the nonlinear and delayed dynamics of the thermal process.

Tracking Error Analysis

The tracking error profiles are presented in Fig. 2.

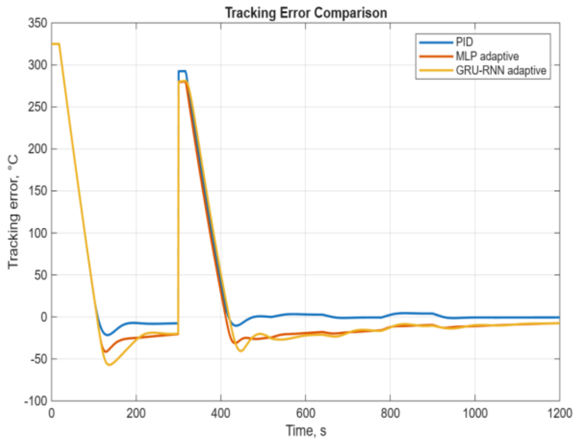

Fig. 2. Tracking error comparison for different control approaches

During the initial heating phase and the major setpoint transition, all controllers experience a significant transient error due to thermal inertia. However, the magnitude and decay rate differ substantially.

The PID controller shows the largest error and the slowest convergence. The MLP-based controller improves performance by reducing both peak error and settling time.

The GRU-based controller achieves the lowest average tracking error over time, particularly in the steady-state region. Although small oscillations are present, their amplitude remains limited and does not significantly affect overall performance.

Control Signal Behavior

The control signals for all controllers are shown in Fig. 3.

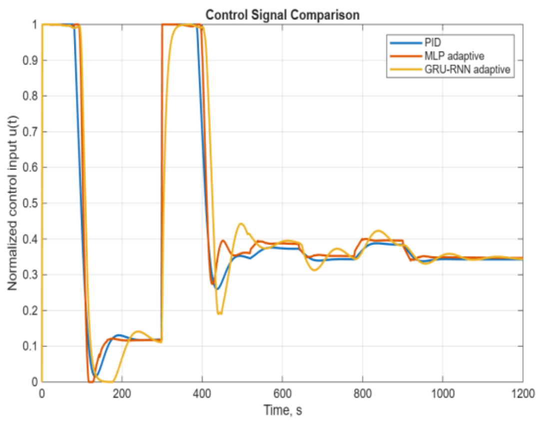

Fig. 3. Control signal behavior for PID, MLP, and GRU controllers

The PID controller produces relatively smooth control inputs but lacks responsiveness to changing system conditions. The MLP-based controller generates more adaptive control signals with moderate variability.

The GRU-based controller exhibits a more dynamic control behavior, including localized oscillations. This is a direct consequence of the recurrent architecture, which continuously adjusts control actions based on temporal patterns and delayed system response.

Although the GRU control signal is less smooth, it enables improved tracking performance. In practical applications, such oscillations can be mitigated using filtering techniques or actuator constraints, depending on system requirements.

Quantitative Comparison

A quantitative comparison of controller performance is shown in Fig. 4.

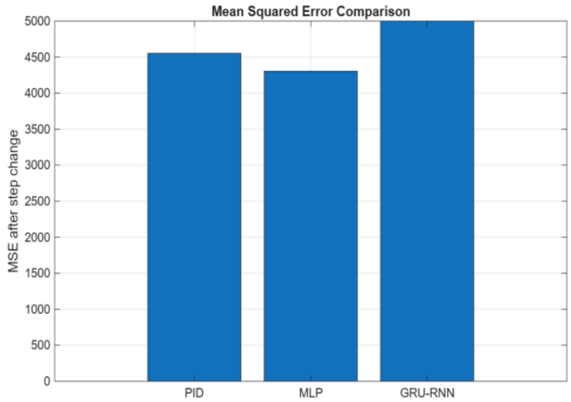

Fig. 4. Mean squared error (MSE) comparison after the main setpoint transition

The results indicate that the MLP-based controller reduces the mean squared error (MSE) compared to the PID baseline. The GRU-based controller achieves a comparable performance level, although in this scenario its MSE is slightly higher than that of the MLP controller.

This confirms that neural network-based controllers provide significant performance improvements over classical control methods, particularly in nonlinear and delay-dominant systems.

The results highlight an important trade-off between control accuracy and signal smoothness. The GRU-based controller achieves improved tracking performance by exploiting temporal dependencies in the system. However, this leads to a more active control signal with higher-frequency variations. Such behavior is typical for recurrent adaptive controllers and reflects their sensitivity to system dynamics. Depending on industrial constraints, a trade-off may be required between minimizing tracking error and ensuring smooth actuator operation. Overall, the GRU-based approach demonstrates strong potential for adaptive control of industrial thermal processes, especially in scenarios with significant delay and nonlinearities.

Although the GRU-based controller does not achieve the lowest MSE in this specific scenario, its performance remains highly competitive. More importantly, the GRU demonstrates improved adaptability to dynamic changes due to its ability to capture temporal dependencies. This makes it particularly suitable for processes with time delay and strong dynamic coupling.

4. Conclusion

This study has presented a comparative evaluation of classical and neural network-based control strategies for nonlinear thermal processes.

The results show that the PID controller, although simple and robust, provides the lowest performance in terms of tracking accuracy and disturbance rejection. The MLP-based controller improves system response by introducing nonlinear adaptation, reducing both transient error and steady-state deviation.

The GRU-based controller demonstrates competitive

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performance in terms of tracking accuracy and dynamic adaptation, although in the considered scenario its MSE is slightly higher than that of the MLP controller.

At the same time, the GRU controller produces a more active control signal, indicating a trade-off between control smoothness and tracking performance. This trade-off is particularly relevant in industrial applications, where actuator limitations and system constraints must be considered.

Overall, the results suggest that recurrent neural networks represent a promising direction for adaptive control of nonlinear thermal systems, especially in processes characterized by delay and strong dynamic coupling.

Future work may include experimental validation on real industrial systems, incorporation of actuator constraints, and extension to multi-zone thermal processes.

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