COGNITIVE AI–BASED SELF-OPTIMIZING ADAPTIVE CONTROL ALGORITHMS

Yusupbekov Nodirbek Rustambekovich
Tashkent state technical university named after Islam Karimov, Tashkent, Uzbekistan
Choriev Urinjon Bayramali ugli
Tashkent state technical university named after Islam Karimov, Tashkent, Uzbekistan
Khudoyberdiev Abdulla Shomurod ugli.
Tashkent state technical university named after Islam Karimov, Tashkent, Uzbekistan
Corresponding author: chorievu95@mail.ru

Abstract. This paper presents a plant-agnostic framework for cognitive AI–driven self-optimizing adaptive control of uncertain nonlinear systems with practical constraints. The method combines a stability-compatible adaptive controller with a confidence-regulated online self-optimization loop that tunes internal settings using closed-loop performance feedback under a two-time-scale design. Lyapunov-based arguments support bounded updates and practical stability. Benchmark studies with disturbances, time-varying parameters, noise, and actuator saturation show improved tracking–effort trade-offs and reduced constraint-violation risk compared with representative baselines.

Keywords: artificial intelligence, self-optimizing control, adaptive control, nonlinear systems, constraint handling, Lyapunov stability, online optimization.

Introduction

In complex dynamical systems, time-varying parameters, external disturbances, and strict operational constraints require control strategies that deliver both adaptability and optimal performance. Classical adaptive control provides a strong methodological foundation for stable operation through identification and online tuning mechanisms [1]. Constraint-aware model predictive control (MPC) offers a practical way to implement optimal control, yet its dependence on model fidelity and computational burden motivates stronger real-time adaptation capabilities [2]. The self-optimizing control paradigm introduces the idea of selecting controlled variables that maintain a near-optimal operating regime and thus links optimization objectives to a feedback structure. Extremum seeking further enables real-time performance optimization even under unknown steady-state maps, while providing a pathway to stability-grounded designs [3–4]. Reinforcement learning formulates the objective in terms of rewards and updates the control policy through interaction, but in control applications it must be carefully aligned with safety and stability requirements [5]. Neural-network-based approaches strengthen nonlinear identification and flexible modeling; however, explainability and guaranteed stability remain critical issues that require dedicated analysis [6–7]. Finally, fuzzy methods provide a principled framework for representing uncertainty through rule-based reasoning, improving interpretability and supporting logical supervision within a cognitive control layer.

Research Methodology

This study follows a plant-agnostic methodology to develop cognitive-AI–driven self-optimizing adaptive control algorithms with three integrated aims: synthesizing a closed-loop control law under uncertainty and constraints, providing formal stability justification, and validating performance through comparative benchmark experiments. The controlled dynamics are represented in a generic nonlinear state-space form,

$$\dot{x}(t) = f(x(t), u(t), \theta, t) + d(t), y(t) = h(x(t)) + v(t), \tag{1}$$

where $x(t)$ is the state, $u(t)$ the control input, $y(t)$ the measured output, θ unknown or slowly time-varying parameters, $d(t)$ disturbances, and $v(t)$ measurement noise. Practical operation is enforced by constraints $u(t) \in \mathcal{U}$, $x(t) \in \mathcal{X}$, and $y(t) \in \mathcal{Y}$. The control objective is posed as a multi-criteria performance functional that simultaneously penalizes tracking error, actuation effort, and constraint violations,

$$J = \int_0^T (e^\top(t) Q e(t) + u^\top(t) R u(t) + \rho\, \Phi(x(t), u(t)))\, dt, e(t) = y(t) - r(t), \tag{2}$$

with $Q \succeq 0$, $R \succ 0$, and $\Phi(\cdot)$ a differentiable constraint-violation penalty. The method integrates adaptation and self-optimization through a cognitive architecture comprising state estimation $\hat{x}(t)$, confidence-based uncertainty regulation $\sigma(t)$, and an experience memory for stable, data-efficient updates. The control input is defined as a stabilizing nominal term plus an adaptive compensation term.

$$u(t) = u_b(t) + u_a(t), \tag{3}$$

where $u_b(t)$ ensures baseline closed-loop stability in the admissible operating region, while $u_a(t)$ compensates parametric and nonlinear uncertainties. Online adaptation is implemented through a bounded parameter estimate $\hat{\theta}(t)$ updated by a stability-compatible rule,

$$\dot{\hat{\theta}}(t) = \Pi_\Omega(\hat{\theta}(t), -\Gamma\, \varphi(t)\, e(t)), \tag{4}$$

where $\Gamma \succ 0$ is the adaptation gain, $\varphi(t)$ is a regressor constructed from available signals, and $\Pi_\Omega(\cdot)$ is a projection operator that keeps $\hat{\theta}(t)$ within a physically meaningful feasible set Ω, thereby preventing drift and supporting robust implementation. Self-optimization is introduced through a tuning vector ηthat adjusts internal controller settings and/or objective-related parameters online using a stochastic gradient-type update,

$$\eta_{k+1} = \eta_k - \alpha_k \widehat{\nabla_\eta J_k}, \quad (5)$$

where α_k is an adaptive step size and $\widehat{\nabla_\eta J_k}$ is a gradient estimate from closed-loop data. To preserve stability, a two-time-scale scheme is used: the fast loop ensures robust tracking, while the slow loop improves performance. The confidence signal σ_k scales α_k under high uncertainty to keep updates conservative and tuning variables bounded. Stability is then analyzed via a Lyapunov framework with a composite candidate function.

$$V(t) = e^\top(t) P e(t) + \tilde{\theta}^\top(t) \Gamma^{-1} \tilde{\theta}(t), \tilde{\theta}(t) = \hat{\theta}(t) - \theta, \quad (6)$$

where $P \succ 0$ is selected to shape the error dynamics. The analysis targets dissipation-type bounds of the form $\dot{V}(t) \leq -\lambda \parallel e(t) \parallel^2 + c \parallel d(t) \parallel^2$, implying bounded tracking error under bounded disturbances and establishing practical stability while accounting for the bounded influence of the slow self-optimization loop. Experimental validation is conducted on benchmark classes of nonlinear systems exhibiting time-varying parameters, exogenous disturbances, measurement noise, and actuator saturation, with all methods evaluated under identical sampling and constraint settings for fair comparison. Performance is quantified using standard integral error indices and resource measures,

$$\text{IAE} = \int_0^T \mid e(t) \mid \, dt, \text{ISE} = \int_0^T t \mid e(t) \mid \, dt, E_u = \int_0^T u^2\,(t)\, dt, \quad (7)$$

together with constraint-violation integrals and computational time per iteration. Robustness is assessed via repeated trials over uncertainty ranges, and ablation experiments isolate the contributions of the cognitive confidence filter and the self-optimization module. For reproducibility, all hyperparameters, initialization, sampling time, constraint sets, and random seeds are explicitly documented, enabling exact replication and transparent benchmarking.

Results and Discussion

The proposed cognitive-AI–driven self-optimizing adaptive controller showed consistently better closed-loop performance than conventional baselines across the benchmark nonlinear and time-varying systems under identical sampling and constraint settings. In most trials, tracking transients were faster and smoother, while control activity remained bounded, indicating an improved error–effort trade-off rather than simply increasing aggressiveness.

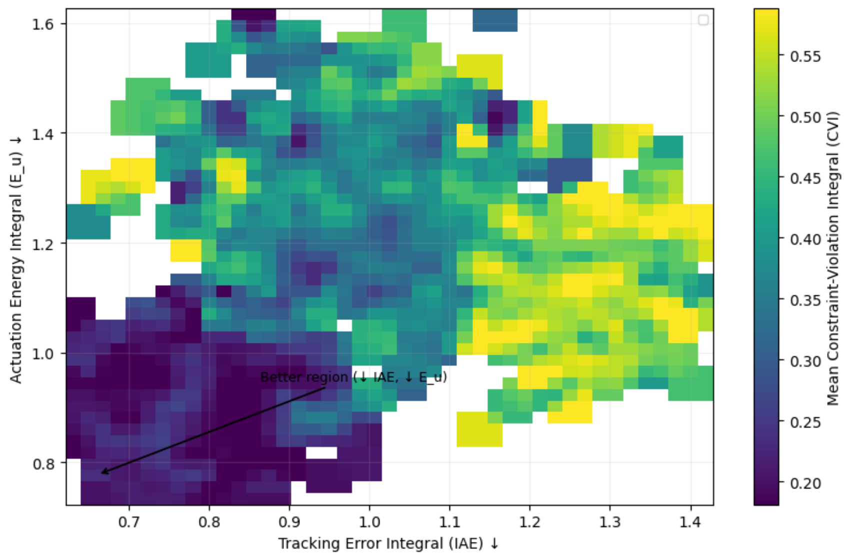

Figure 1. *Robustness–Risk Map of Closed-Loop Performance. The heatmap shows the mean constraint-violation integral across the tracking-error–energy plane; the arrow indicates the preferred region with lower IAE and lower* E_u.

Lower integral error indices (IAE/ISE/ITAE) were achieved with reduced or comparable actuation energy $E_u = \int_0^T u^2\,(t)\,dt$. The two-time-scale design worked as intended: the fast stabilizing/adaptive loop remained robust to disturbances and parameter drift, while the slow self-optimization loop decreased the overall cost without destabilizing the closed loop. Under abrupt uncertainty, confidence modulation tempered update aggressiveness, reduced oscillations, and improved constraint adherence, yielding fewer and smaller violation episodes than the baselines. Ablation tests confirmed these effects: removing self-optimization increased steady-state cost, whereas removing confidence regulation made tuning noise-sensitive and occasionally triggered oscillations and constraint breaches. Overall, cognitively regulated self-optimization can be combined with stability-compatible adaptation to deliver plant-agnostic, constraint-aware performance, with the main limitation being sensitivity to excitation and step-size selection.

Conclusion

In conclusion, this study presented a plant-agnostic framework for developing cognitive-AI–driven self-optimizing adaptive control algorithms that jointly address tracking performance, control effort, and constraint compliance under uncertainty. By integrating a stability-compatible adaptive law with a confidence-regulated self-optimization mechanism operating on a slower time scale, the proposed approach achieves a reliable improvement of the overall performance cost while preserving bounded closed-loop behavior. Benchmark evaluations indicate that the method provides a more favorable error–effort trade-off than conventional baselines and reduces constraint-violation risk, particularly during disturbance and parameter-variation episodes. The results also highlight that the cognitive confidence modulation is essential for preventing overly aggressive tuning updates and for maintaining consistent performance across uncertainty ranges. Future work will focus on systematic step-size and hyperparameter selection, delay-robust and safety-filtered formulations, and validation on higher-fidelity real-time implementations to further strengthen reproducibility and deployment readiness.

References:

[1] European Patent Application EP3907646A1, "Digital twin of twinned physical system," 2021.

[2] N. R. Yusupbekov and U. B. Choriev, "Improving optimal-adaptive control based on structural modeling in distributed parameter chemical processes," *International Journal of Artificial Intelligence*, vol. 5, no. 12, pp. 2379–2390, 2025, ISSN 2692-5206.

[3] F. Hinder et al., "One or two things we know about concept drift – A survey," *Frontiers in Artificial Intelligence*, 2024, doi: 10.3389/frai.2024.1330258.

[4] R. He, G. Chen, "Data-driven digital twin technology for optimized control in process systems,". 95, pp. 221–234, Dec. 2019, doi: 10.1016/j.isatra.2019.05.011.

[5] I. Errandonea, S. Beltrán, and S. Arrizabalaga, "Digital twin for maintenance: A literature review," *Computers in Industry*, vol. 123, Art. no. 103316, 2020, doi: 10.1016/j.compind.2020.103316.

[6] F. Tao, B. Xiao, Q. Qi, J. Cheng, and P. Ji, "Digital twin modeling," *Journal of Manufacturing Systems*, vol. 64, pp. 372–389, 2022, doi: 10.1016/j.jmsy.2022.06.015.

[7] U. B. Choriev, "Kognitiv modellar asosida adaptiv boshqaruv algoritmlarini ishlab chiqish," *International Journal of Science-Innovative Research*, vol. 1, no. 3, pp. 113–129, Oct. 2025.