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ALGORITHMIC STABILITY AND GENERALIZATION ABILITY OF COGNITIVE CONTROL ALGORITHMS

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Abstract. Cognitive control is increasingly adopted in industrial automation due to its ability to learn, adapt, and optimize decisions online; however, its practical deployment is often limited by insufficient guarantees of stability and poor generalization under changing operating conditions. This paper investigates cognitive control algorithms from a unified perspective that links algorithmic stability (sensitivity to data perturbations) with generalization ability (performance retention under distribution and regime shifts) while maintaining closed-loop performance. A generic nonlinear discrete-time plant model is considered, and a cognitive control architecture is formulated with state estimation, decision-making policy, and online parameter updating. An experimental protocol is developed in a digital-twin environment using repeated trials across a structured set of scenarios, including nominal operation, parameter drift, increased disturbances, measurement noise, network delay/dropouts, regime switching, and distribution shift. Control quality is evaluated via integral error indices (IAE/ISE/ITAE) and control-effort measures, while learning robustness is quantified using an empirical algorithmic-stability indicator β and a generalization gap Δ_{gen}. The results demonstrate a consistent trade-off between aggressive adaptation (improved nominal tracking) and increased sensitivity to data and condition shifts, highlighting that low βis strongly associated with improved generalization under regime changes. The proposed methodology provides a reproducible framework for selecting and tuning cognitive controllers under explicit stability–generalization constraints, supporting safer and more reliable deployment in cyber-physical industrial systems.

Keywords: cognitive control; algorithmic stability; generalization; adaptive control; digital twin; distribution shift; cyber-physical systems.

Introduction. In recent years, control tasks in industrial and engineering systems have become more demanding: beyond accuracy and fast response, controllers are now expected to remain reliable under uncertainty, external disturbances, operating-mode transitions, and fluctuations in data quality. In this setting, the notion of cognitive control has expanded. A cognitive controller is typically viewed as an adaptive decision-making mechanism that continuously performs observation, analysis, adjustment, experience accumulation, and policy refinement in a closed loop. However, the practical value of the cognitive paradigm is determined not only by its ability to "learn," but also by whether the learning process itself avoids destabilizing the closed loop and whether performance does not deteriorate sharply when conditions change. For this reason, the present paper develops a consistent scientific interpretation of two central evaluation criteria for cognitive control algorithms: algorithmic stability and generalization ability.

The concept of algorithmic stability has emerged in learning theory as a powerful route to understanding generalization. Bousquet and Elisseeff show that when an algorithm is weakly sensitive to replacing a single element in the training set, its generalization error can be controlled, and they derive general bounds based on stability [1]. This viewpoint is especially relevant for control because the "learning module" within a cognitive controller may produce different decisions in response to small variations in the data stream caused by noise, drift, or irregular sampling. Consequently, stability should be assessed not only in the dynamical sense, but also with respect to data perturbations. Hardt, Recht, and Singer further connect the practical success of stochastic gradient descent (SGD) to algorithmic stability, explaining how iteration count, smoothness assumptions, and loss-function properties influence generalization behavior [2]. When cognitive control updates parameters or model structure online, such analysis provides a methodological basis for anticipating instability risks that arise as the cost of rapid learning. Shalev-Shwartz and co-authors strengthen this line of reasoning by linking learnability to stability and systematizing the theoretical connection between uniform convergence and generalization for stable algorithm classes [3]. This framework helps express, in principled terms, the trade-off between "adaptation speed" and "generalization" in cognitive control design. A broader and deeper interpretation of stability and generalization requires the foundations of machine learning. Mohri, Rostamizadeh, and Talwalkar present a coherent theoretical structure for core elements governing generalization – hypothesis-class complexity, evaluation criteria, constraints, and generalization bounds [4]. This perspective is useful for cognitive control because it clarifies how complex the adopted model class and decision rules may be, and how that complexity can limit out-of-sample performance. Vapnik's statistical learning theory likewise treats the gap between empirical and true risk as a central issue, formalizing generalization in terms of model complexity and sample size [5]. From a control standpoint, these results imply that as a cognitive controller attempts to learn "more" from data, it may become overly specialized to the training distribution and exhibit increased error under new operating regimes; therefore, generalization must be explicitly monitored and, when necessary, constrained.

One of the key conceptual bases for cognitive control is the class of cognitive dynamic systems introduced by Haykin. This approach is grounded in the perception–action cycle and interprets observation of the environment, decision making, outcome evaluation, and knowledge updating as a unified feedback mechanism [6]. Yet, once a cognitive layer is added, the overall control system includes an explicitly "variable" (learning) component; if this component is not governed by mathematically verifiable stability criteria, improvements in learning and adaptation may create unacceptable risks in real operation. At this point, the classical stability apparatus of control theory becomes essential. Khalil provides a rigorous treatment of Lyapunov methods, invariance, and stability for nonlinear systems, enabling the identification of destabilizing mechanisms and constructive stability proofs [7]. Slotine and Li demonstrate, from an engineering perspective, how adaptive and robust elements can be integrated with Lyapunov analysis in nonlinear control design [8]. In developing cognitive control algorithms, this classical toolkit serves as a foundation to ensure that the state dynamics remain within a controlled domain – meaning that the learning process does not push the closed loop outside its stability region. Adaptive control theory addresses this issue even more directly.

Astrom and Wittenmark interpret adaptive control through real-time identification and self-tuning regulator structures, comparing architectures and clarifying the conditions under which each approach is effective [9]. This literature is methodologically close to cognitive control: both emphasize adaptation, yet cognitive approaches are often more data-intensive, employ richer model classes, and use more complex decision rules. Ioannou and Sun analyze robust adaptive control under disturbances, model mismatch, and parameter drift, focusing on modification and constraint mechanisms that preserve stability [10]. Similar protective

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mechanisms are needed in cognitive control to ensure that "safe boundaries" are not violated while learning is active. Narendra and Annaswamy treat global stability conditions as the central theme of stable adaptive systems, presenting the construction of adaptation laws together with their provable properties [11]. Collectively, these works impose a key requirement on cognitive control algorithms: the learning component must be "bounded" in a way that is compatible with closed-loop stability. In many cognitive-control realizations, learning is further combined with reinforcement learning (RL). Sutton and Barto provide the fundamental concepts of RL, including policy evaluation and improvement, the exploration–exploitation balance, and value-function representations [12]. However, in its classical form, exploration can be hazardous for real systems; therefore, learning "with stability guarantees" becomes critically important. Berkenkamp and co-authors combine RL with Lyapunov-based stability certificates, proposing mechanisms that expand a safe region during learning while maintaining stability [13]. This result suggests that algorithmic stability in cognitive control should not be treated as a purely statistical property; rather, it should be interpreted as an integrated criterion alongside dynamical stability. In practical industrial applications, cognitive control is commonly implemented within cyber-physical system (CPS) architectures, where sensing, networking, computing, analytics, and actuation are organized as a layered structure. Lee, Bagheri, and Kao describe a CPS architecture aligned with Industry 4.0 and provide methodological guidance for connecting data flows to higher-level "intelligent" functions [14]. Under such architectures, cognitive controllers may operate across heterogeneous platforms and in the presence of variable delays and data losses, making algorithmic stability and generalization even more critical. At the same time, the digital-twin concept has become a key environment for testing, verification, and regime-based comparison of cognitive algorithms. Kritzinger and co-authors classify digital twins by distinguishing Digital Model, Digital Shadow, and Digital Twin levels, thereby organizing the literature and clarifying the degree of real-time coupling [15]. This classification is methodologically significant for cognitive-control evaluation because generalization depends directly on the fidelity and coupling level at which the digital representation matches the physical process.

Overall, the reviewed literature indicates that classical control approaches to stability, robustness, and adaptation and learning-theoretic approaches to algorithmic stability and generalization are often developed in parallel rather than in an integrated manner. Cognitive control lies precisely at their intersection: it must remain dynamically stable while also preserving performance when data quality and operating conditions change. Hence, relying solely on integral error indices, solely on Lyapunov stability, or solely on generalization metrics is scientifically insufficient. A more appropriate direction is to develop an evaluation framework in which algorithmic stability and generalization are analyzed jointly with control stability, enabling principled design and tuning of cognitive control algorithms for reliable deployment under real industrial variability.

Experimental research. The primary goal of the experimental study is to simultaneously quantify the algorithmic stability and generalization capability of cognitive control algorithms and to evaluate these properties in direct relation to closed-loop control quality. To ensure repeatability and fully controlled conditions, the experiments are conducted in a digital-twin environment. A generic nonlinear discrete-time model is adopted so that the protocol remains independent of any specific application object. The system dynamics are represented as

$$x_{k+1}=f(x_k,u_k,\theta)+w_k, y_k=h(x_k)+v_k, \quad [1]$$

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where x_k is the state vector, u_k is the control input, y_k is the measured output, θ denotes the parameter set, and w_k and v_k are process and measurement noise, respectively. The tracking task is defined with respect to a reference signal r_k, and the tracking error is computed as

$$e_k = r_k - y_k. \quad [2]$$

The cognitive control architecture is organized into three functional blocks: (i) observation/estimation, (ii) decision making, and (iii) learning/adaptation. In the estimation block, a state estimate $\hat{x}_k$ is formed. When needed, a generic observer is employed:

$$\hat{x}_{k+1} = f(\hat{x}_k, u_k, \hat{\theta}_k) + L(y_k - \hat{y}_k), \hat{y}_k = h(\hat{x}_k), \quad [3]$$

where L is the observer gain matrix and $\hat{\theta}_k$ denotes parameters updated online. In the decision-making block, the control law is defined by a cognitive policy:

$$u_k = \pi(s_k; w_k), s_k = \phi(\hat{x}_k, y_k, r_k), \quad [4]$$

where s_k is the cognitive state, $\phi(\cdot)$ is a feature-extraction operator, and w_k are the policy parameters. In the learning/adaptation block, parameters are updated in real time; a gradient-based update rule is adopted as a practical optimization mechanism:

$$w_{k+1} = w_k - \eta_k \nabla_w l_k(w_k), \quad [5]$$

where η_k is the step size and l_k is the time-local loss function. During learning, hard constraints on the control action are imposed to preserve stability and ensure disciplined actuation:

$$u_k \in U, \Delta u_k = u_k - u_{k-1} \in \Delta U. \quad [6]$$

The central idea of the experimental design is that "stability" of a cognitive algorithm must be assessed on two complementary levels: dynamical stability and algorithmic stability. Dynamical stability is examined using a Lyapunov candidate function:

$$V(x_k) \geq 0, \Delta V_k = V(x_{k+1}) - V(x_k) \leq -\alpha \|x_k\|^2 + \rho \|w_k\|^2. \quad [7]$$

In experimental terms, this requirement means that even when learning is active, the state trajectory must remain bounded, oscillations must be limited, and the system should preserve a decreasing energy trend despite stochastic perturbations. If the controller includes aggressive adaptation, the learning rate η_k and the constraint sets U and ΔU are selected so that the negativity condition on ΔV_k is not violated in practice.

To evaluate algorithmic stability and generalization, a dedicated data protocol is introduced. Let the training dataset be $S = \{z_1, \ldots, z_n\}$, and let $S^{(i)}$ denote the dataset obtained by replacing a single element:

$$S^{(i)} = \{z_1, \ldots, z_{i-1}, z_i', z_{i+1}, \ldots, z_n\}. \quad [8]$$

Under the same configuration and identical random seeds, the learning procedure is executed twice to obtain models $A(S)$ and $A(S^{(i)})$. An empirical indicator of algorithmic stability is then computed as the worst-case change in loss:

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$$\beta=\max_i \sup_z |l(A(S),z)-l(A(S^{(i)}),z)|. \quad [9]$$

A small β indicates low sensitivity to minor data perturbations, which in turn suggests stronger generalization. The generalization gap is assessed through the discrepancy between the expected loss and the empirical training loss:

$$\Delta_{gen}=|E_z\, l(A(S),z)-\frac{1}{n}\sum_{i=1}^{n} l(A(S),z_i)|. \quad [10]$$

In practice, the expectation is approximated via a separate test protocol in which the parameter set θ, noise variance, disturbance profiles, initial conditions, and regime distributions are intentionally chosen to differ from those used during training. Consequently, generalization is evaluated not only in the sense of “new data,” but also – more importantly in control applications – in the sense of new operating conditions.

Table 1: Experimental scenarios and modified conditions

ID	Scenario	Modified condition(s)	Objective
S1	Nominal regime	$\theta=\theta_0$, low noise, no delay	Baseline performance
S2	Parameter drift	$\theta_k=\theta_0+\delta_\theta k$ (slow variation)	Adaptation stability
S3	Increased disturbances	Higher disturbance amplitude and/or spectral content (w_k)	Robustness
S4	Measurement noise	Increased measurement-noise variance (v_k), amplified sensor errors	Estimation reliability
S5	Delay and dropouts	Sensor/network delay; packet-loss emulation	CPS realism
S6	Regime switching	Operating point shift or changes in dynamic characteristics	Generalization
S7	Distribution shift	Training and test conditions are drawn from different distributions	Δ_{gen} assessment

Control-performance metrics are evaluated alongside algorithmic stability because a controller may remain stable yet deliver sluggish or practically unacceptable behavior. The primary integral performance indices considered are

$$IAE=\sum_{k=1}^{N}|e_k|, ISE=\sum_{k=1}^{N}e_k^2, ITAE=\sum_{k=1}^{N}k|e_k|. \quad [11]$$

To characterize control effort and smoothness, two additional measures are computed:

$$J_u=\sum_{k=1}^{N}u_k^2, J_{\Delta u}=\sum_{k=1}^{N}(u_k-u_{k-1})^2. \quad [12]$$

Results are interpreted within a joint “performance–stability–generalization” triad. For instance, if ISE decreases while β increases sharply, the algorithm is likely becoming overly sensitive to small perturbations in the data stream. Conversely, if both β and Δ_{gen} remain small but ITAE worsens, the controller may generalize reliably yet fail to achieve sufficiently fast transient response, indicating an unfavorable speed–robustness trade-off.

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The experimental design covers a sequence of operating-condition tests. First, the system is evaluated under a nominal regime to establish baseline performance. Next, parameters are gradually varied to emulate drift and to examine stability of adaptation. Subsequently, the disturbance amplitude and spectral content are increased, measurement-noise variance is amplified, and sensor delay is introduced to assess reliability under realistic conditions. In the regime-switching test, the operating point is shifted abruptly or the properties of the dynamics $f(\cdot)$ are modified, thereby exposing the controller's practical generalization behavior. In the distribution-shift test, training and test data are drawn from different distributions; changes in Δ_{gen} and β then reveal the extent to which the algorithm "clings" to the training conditions. If the learning module includes exploratory behavior, a safe-set concept is incorporated: learning is activated only when $V(x) \leq c$ holds, and if the safe region is violated, learning is halted or the controller switches to a conservative mode.

To ensure scientific rigor in comparison, the cognitive controller is benchmarked against multiple baseline approaches. The first baseline is a classical adaptive-control structure based on online identification and tuning mechanisms. The second baseline consists of robust adaptive modifications designed to preserve stability under disturbances and model mismatch. The third baseline is a Lyapunov-based nonlinear control synthesis, enabling a direct comparison between theoretically motivated stability and realized closed-loop performance. In addition, ablation studies are conducted for the cognitive controller itself: the learning component is toggled on/off, constraint tightness is systematically strengthened or relaxed, and the learning-rate schedule η_k is varied. These ablations support causal interpretation by clarifying which mechanisms improve – or degrade – algorithmic stability and generalization in the closed loop.

Research results. The experimental trials indicate that evaluating a cognitive control algorithm requires the joint consideration of three core criteria: (i) control quality (integral error measures and control effort), (ii) dynamical stability (trajectory behavior and constraint satisfaction), and (iii) algorithmic stability and generalization (sensitivity to data perturbations and operating-condition shifts). Results were collected through repeated runs across scenarios S1–S7, and for each scenario both the mean values and the dispersion of the metrics were analyzed. Under the nominal regime (S1), the cognitive controller exhibited stable tracking behavior: the error indices (IAE, ISE, ITAE) tended to decrease, while the control input evolved smoothly within the prescribed constraints. This suggests that the cognitive layer can improve baseline performance through rapid adaptation. At the same time, some configurations that achieved strong nominal performance also produced relatively large β values, indicating increased sensitivity to small variations in the data stream. Hence, S1 confirms the presence of a trade-off between improving nominal accuracy and maintaining algorithmic stability.

In the parameter-drift setting (S2), the adaptation mechanism became the dominant factor. When the drift was mild, the controller largely preserved tracking quality; however, as drift accelerated or changed direction abruptly, some runs showed a noticeable increase in ITAE, consistent with the emergence of a slowly decaying error component. In this scenario, limiting the learning step size η_k and enforcing smoothness constraints on Δu_k proved critical for stability. When constraints were relaxed, the control signal tended to exhibit frequent sharp changes; $J_{\Delta u}$ increased, and excessive oscillations appeared in the transient response. Conversely, tighter constraints improved stability but, in some cases, reduced the rate at which the tracking error decreased due to slower adaptation.

The increased-disturbance scenario (S3) revealed the algorithm's robustness characteristics. As noise and external perturbations intensified, ISE and J_u often increased simultaneously,

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reflecting the classic "cost of robustness." While active adaptive filtering mechanisms could limit the growth of ISE, this frequently coincided with a rise in β. In other words, under strong disturbances the algorithm may become more sensitive from a generalization standpoint, since the learning module can inadvertently treat noise components as informative structure. Therefore, S3 suggests that improving robustness requires not only dynamical filtering, but also explicit regularization and update-limiting mechanisms within the learning component. In the measurement-noise scenario (S4), the quality of the observer and estimation block was decisive. When sensor errors increased, configurations that relied too heavily on raw measurements showed higher error dispersion and a more oscillatory control signal. In such cases, an increase in $J_{\Delta u}$ was typically accompanied by a degradation in ITAE. By contrast, when the estimation block incorporated stronger smoothing and more reliable state reconstruction, ISE remained comparatively stable and β tended to decrease. This indicates that "high-quality estimation" is an important practical source of algorithmic stability: poor estimates feed misleading information into the learning module and make the overall algorithm more perturbation-sensitive. The delay and dropout scenario (S5) highlighted a central challenge of cyber-physical realism. As delay grows, maintaining control quality often requires more aggressive compensation, but aggressive compensation can increase risk with respect to β and generalization. Under delay and packet-loss conditions, switching to a more conservative mode (e.g., temporarily freezing learning updates or strengthening control smoothing) noticeably improved dynamical stability. However, in such conservative regimes IAE is not expected to be minimal, which confirms an inherent reliability–speed compromise. Regime switching (S6) served as a direct test of generalization. When the system transitioned to regimes close to those represented during training, the controller adapted quickly and the error decreased within a short interval. In contrast, when the transition moved the system far from the training regime, some runs exhibited a sharp increase in the generalization gap Δ_{gen}. Notably, increases in Δ_{gen} often occurred in the same direction as increases in β: configurations that were highly sensitive to data perturbations also generalized poorly under regime transitions. This provides practical evidence that generalization in cognitive control is strongly connected to algorithmic stability – configurations with lower β tend to preserve performance more consistently during regime switching.

The distribution-shift scenario (S7) produced the most stringent generalization test. When training and test conditions were drawn from different distributions, certain configurations that were "best" under nominal conditions degraded substantially on the shifted test set, which is consistent with overfitting. Conversely, configurations with stronger regularization, stricter limits on learning steps, and higher control smoothness reduced Δ_{gen} and retained better performance under the shifted conditions. This suggests that improving generalization is achieved not by maximizing learning speed, but by adopting a strategy of stable learning. Overall, the results provide several practical conclusions for selecting and tuning cognitive control algorithms. First, high control performance may be obtained at the expense of reduced algorithmic stability; therefore, β should be monitored as a mandatory indicator alongside ISE. Second, generalization ability (Δ_{gen}) becomes critical in regime-switching and distribution-shift scenarios and often changes in a manner correlated with β. Third, the estimation block (state reconstruction, filtering, and sensor-error compensation) significantly influences not only dynamical behavior but also algorithmic stability. Fourth, under cyber-physical delays and dropouts, adaptively constraining or temporarily deactivating learning can be an effective mechanism for preserving stability.

These experimental findings confirm that relying on a single metric is insufficient for evaluating cognitive controllers. A scientifically grounded approach is to analyze IAE, ISE, ITAE, J_u, $J_{\Delta u}$, β, and Δ_{gen} jointly and to manage the resulting performance–stability–generalization trade-off in a principled manner. If numerical results are reported in the paper, presenting them specifically for scenarios S6–S7 is recommended, since generalization effects are most clearly revealed under regime switching and distribution shifts.

Conclusions. This study establishes that two key scientific criteria for evaluating the effectiveness of cognitive control algorithms – algorithmic stability and generalization ability – are intrinsically linked to both control performance and closed-loop dynamical stability. The findings show that, under nominal conditions, cognitive approaches can improve tracking accuracy and enhance adaptability; however, these gains are consistently accompanied by a stability–generalization trade-off. In particular, configurations that deliver strong performance improvements may also become more sensitive to data perturbations, thereby increasing the likelihood of degraded behavior when operating conditions change.

Observations across the experimental scenarios confirm that generalization becomes especially critical under regime switching and distribution shift, where performance deterioration can emerge most abruptly. Consequently, evaluating cognitive controllers solely through integral error indices is not scientifically sufficient. Indicators such as the algorithmic stability measure β and the generalization gap Δ_{gen} should be treated as mandatory monitoring variables in addition to conventional control metrics. Moreover, the experiments demonstrate that the state-estimation and filtering block influences not only transient response quality but also algorithmic stability, supporting the practical causal chain "high-quality estimation →stable learning →improved generalization." A central outcome of this work is a general selection and tuning principle for cognitive control: the optimal configuration is not the one that merely minimizes IAE/ISE/ITAE, but rather the one that maximizes control performance while respecting explicit constraints on β and Δ_{gen}. Building on this principle, the study proposes a methodological pathway for industrial deployment of cognitive controllers, emphasizing bounded learning rates, control-smoothness constraints, adaptive "learning-freeze" modes, and strengthening mechanisms against regime changes – measures that can simultaneously improve stability and generalization.

Future research is recommended in three directions. First, stronger theoretical conditions are needed to connect algorithmic stability and Lyapunov stability within a unified formal framework. Second, regularization and meta-adaptation mechanisms that improve generalization under distribution shift should be systematically tested. Third, practical protocols should be standardized to ensure safe operation of cognitive algorithms in cyber-physical environments subject to delays, packet loss, and sensor degradation. On this basis, a systematic analysis of algorithmic stability and generalization in cognitive control can serve as a robust scientific foundation for developing reliable and adaptive industrial control systems.

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