

# Towards a Unified Theory of Self-Adaptation in Software-Intensive Systems

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**ABSTRACT:** Self-adaptive systems (SAS) are designed to dynamically adjust their behavior in response to changing environments, uncertainties, and evolving requirements. Despite significant advances in adaptive software engineering, the field remains fragmented, with multiple adaptation paradigms (e.g., control-theoretic, rule-based, learning-driven) operating in isolation. This paper proposes a unified theory of self-adaptation that integrates these diverse approaches into a coherent framework. We identify key principles—such as feedback loops, uncertainty handling, and goal-driven adaptation—and formalize a meta-model that generalizes existing adaptation mechanisms. We evaluate our theory through case studies in cloud computing, IoT, and autonomous robotics, demonstrating its applicability across domains. Our work bridges gaps between isolated adaptation strategies and provides a foundation for more robust and scalable self-adaptive systems.

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## I. INTRODUCTION

Modern software-intensive systems, ranging from large-scale cloud platforms to embedded IoT networks and autonomous robotics, operate in increasingly complex and unpredictable environments. These systems must continuously adapt to fluctuating workloads, hardware failures, security threats, and evolving user requirements without human intervention. Self-adaptive systems (SAS) address this challenge by autonomously modifying their behavior at runtime, leveraging techniques such as feedback control, rule-based policies, and machine learning-driven decision-making. Despite decades of research, however, the field remains fragmented, with different adaptation paradigms developed in isolation, each with its own assumptions, strengths, and limitations.

A key challenge in self-adaptive software engineering is the lack of a unifying theoretical foundation that can integrate diverse adaptation strategies into a coherent framework. Control-theoretic approaches, such as the MAPE-K (Monitor-Analyze-Plan-Execute over Knowledge) loop, provide formal guarantees on system stability but struggle with high-dimensional, uncertain environments. Rule-based adaptation offers interpretability but becomes unwieldy as system complexity grows. Meanwhile, modern machine learning techniques, particularly reinforcement learning, enable sophisticated adaptation in dynamic settings but often lack formal verifiability and may exhibit unpredictable behaviors. The absence of a common model hinders interoperability, limits reuse, and makes it difficult to reason about the combined effects of multiple adaptation mechanisms.

This paper seeks to bridge this gap by proposing a unified theory of self-adaptation for software-intensive systems. Rather than treating different adaptation strategies as competing alternatives, we develop a meta-model that generalizes their underlying principles, enabling systematic integration and comparison. Our approach builds on three foundational concepts: feedback-driven control for continuous adaptation, explicit goal representations to guide decision-making, and probabilistic uncertainty modeling to enhance robustness in open-world scenarios. By formalizing these elements into a state-transition framework, we provide a common language for describing and analyzing self-adaptive behaviors across domains.

To demonstrate the practical applicability of our theory, we evaluate it in three real-world case studies: cloud autoscaling, IoT fault recovery, and autonomous drone navigation. These examples illustrate how different adaptation strategies—when grounded in a unified model—can complement rather than compete with one another. For instance, combining control-theoretic stability guarantees with data-driven learning improves both reliability and efficiency in cloud resource management. Similarly, integrating probabilistic reasoning with rule-based policies enhances resilience in distributed IoT systems. Our results suggest that a unified theoretical foundation not only advances the design of self-adaptive systems but also facilitates the development of more maintainable, scalable, and verifiable solutions.

The contributions of this work extend beyond theoretical formalization. By establishing a common

framework, we enable new research directions in cross-domain adaptation, hybrid human-AI control, and ethical governance of autonomous systems. Future work could explore how our model supports the composition of multiple adaptation mechanisms, how it interacts with human oversight, and how it can be extended to address emerging challenges such as adversarial resilience and explainable AI. Ultimately, this paper aims to shift the discourse in self-adaptive systems from fragmented techniques to a more principled, holistic understanding of adaptation in software engineering.

## **II. BACKGROUND AND RELATED WORK**

The study of self-adaptive systems has evolved significantly over the past three decades, drawing from diverse disciplines including control theory, artificial intelligence, and software engineering. As computing systems have grown more complex and interconnected, the need for autonomous adaptation mechanisms has become increasingly critical. This section first provides an overview of the historical development and key concepts in self-adaptation research, then examines the major paradigms that have emerged, and finally discusses the limitations of current approaches that motivate our unified theory.

### **2.1 Self-Adaptation Paradigms**

Three primary paradigms have dominated research in self-adaptive systems, each offering distinct advantages and particular challenges in different application contexts.

Self-adaptive systems (SAS) employ diverse methodologies to achieve dynamic behavior adjustment in response to environmental changes. Recent advancements have refined these paradigms, enhancing their applicability across domains such as cloud computing, IoT, and autonomous systems. Below we detail three primary adaptation paradigms, supported by contemporary research.

#### **2.1.1 Control-Theoretic Adaptation**

Control-theoretic approaches remain foundational in self-adaptive systems, leveraging feedback loops and stability guarantees for reliable adaptation. Recent work extends classical MAPE-K (Monitor-Analyze-Plan-Execute over Knowledge) architectures with probabilistic modeling to handle uncertainty. For instance, Vogel et al. propose an online self-adaptation framework for stream processing that dynamically adjusts parallel patterns while ensuring smooth reconfiguration transitions [1]. Similarly, Affonso et al. introduce a reflection-based reference architecture (RA4SaS) that formalizes controlled adaptation through automated runtime adjustments [2]. These methods excel in structured environments but face challenges in highly dynamic, nonlinear systems where traditional control models may struggle.

#### **2.1.2 Rule-Based Adaptation**

Rule-based systems rely on predefined policies (e.g., event-condition-action rules) to govern adaptation. While interpretable, they often lack scalability in complex, open-world scenarios. Recent innovations incorporate hybrid architectures to mitigate these limitations. For example, Li et al. propose a two-layer adaptation framework inspired by attribution theory, separating environment-agnostic logic (internal causes) from context-specific rules (external causes) [3]. This approach improves reusability while maintaining transparency, though challenges persist in handling unforeseen conditions not covered by rule sets.

#### **2.1.3 Machine Learning-Driven Adaptation**

Machine learning (ML), particularly reinforcement learning (RL), has emerged as a powerful paradigm for adaptive systems operating in uncertain environments. Qian et al. present MetaAgent, a self-evolving model that refines tool-use strategies through continuous experience without parameter retraining [4]. In Machine Learning-Enabled Systems (MLES), QoS-aware model switching (e.g., AdaMLS) combines lightweight unsupervised learning with MAPE-K extensions to balance performance and uncertainty [5]. These methods excel in high-dimensional state spaces but require robust safety verification to prevent undesirable emergent behaviors.

### **2.2 Limitations of Current Approaches**

Current self-adaptation paradigms suffer from a lack of unified theoretical underpinnings. Control-theoretic approaches, while providing formal stability guarantees, often rely on oversimplified linear system assumptions that fail in complex, nonlinear environments [6]. Rule-based systems, despite their interpretability, struggle with scalability in open-world scenarios where predefined policies cannot efficiently handle emergent behaviors [7]. Meanwhile, machine learning-driven methods, particularly reinforcement learning, offer flexibility but lack rigorous formal verification frameworks, raising concerns about safety and reliability in critical applications [8].

The practical deployment of self-adaptive systems reveals significant engineering hurdles. A key issue is the prevalence of cascading failures, where unintended interactions between multiple control loops lead to system breakdowns. Studies of industrial deployments show that 68% of incidents stem from poorly coordinated adaptation mechanisms [9]. Additionally, machine learning-based adaptation imposes substantial computational

overhead, consuming up to 30% of system resources in edge computing scenarios [10]. This is particularly problematic for real-time applications where efficiency is critical. Another fundamental challenge is the uncertainty paradox, where the effectiveness of adaptation strategies diminishes as environmental unpredictability increases [11]. This paradox arises because most adaptation mechanisms rely on historical data or predefined policies, which become less reliable in highly dynamic settings.

The evaluation of self-adaptive systems remains inconsistent across the field. Recent analyses indicate that only 22% of published evaluations use real-world deployment scenarios, with the majority relying on simulations that may not capture operational complexities [12]. Longitudinal studies are exceptionally rare, despite evidence that adaptation effectiveness deteriorates over time due to concept drift and environmental shifts [13]. The absence of standardized benchmarks makes it difficult to objectively compare different approaches, hindering progress in the field.

Recent work has begun addressing these limitations through hybrid approaches. Neuro-symbolic integration combines the verifiability of rule-based systems with the flexibility of machine learning, offering a promising path forward [14]. Probabilistic formal methods are being developed to provide guarantees about adaptation outcomes under uncertainty [15]. Additionally, new standardized benchmarking frameworks such as SASBench incorporate realistic failure modes and uncertainty profiles, enabling more rigorous evaluation [16]. These advances suggest that future SAS research should focus on bridging the gap between theoretical rigor and practical deployability, while developing robust evaluation methodologies that reflect real-world conditions.

### **III. A UNIFIED THEORY OF SELF-ADAPTATION**

The fragmentation of current self-adaptation approaches calls for a comprehensive theoretical framework that can bridge different paradigms while addressing their individual limitations. A unified theory of self-adaptation should not only integrate existing methods but also provide foundational principles for developing novel adaptation strategies that are both theoretically sound and practically viable. This section presents such a framework, beginning with its core principles before detailing its formal model and practical applications.

#### **3.1 Core Principles**

The proposed unified theory of self-adaptation is built upon three fundamental principles that collectively address the limitations of existing approaches while enabling more robust and generalizable adaptation mechanisms. These principles emerge from a synthesis of insights across multiple disciplines, carefully balancing theoretical rigor with practical applicability in real-world systems.

The first principle, feedback-driven adaptation, establishes a continuous cycle of monitoring, analysis, decision-making, and execution that forms the backbone of all self-adaptive systems. Unlike traditional approaches that treat these phases as distinct, our framework emphasizes their tight integration and dynamic interplay, allowing for more responsive and context-aware adaptations. This principle extends beyond simple control loops to incorporate multi-timescale feedback mechanisms that can operate simultaneously at different levels of system granularity.

The second principle, goal-aware adaptation, introduces an explicit representation of system objectives and constraints that guides all adaptation decisions. Rather than relying on predefined rules or learned behaviors alone, this principle maintains a dynamic model of system goals that can evolve with changing requirements and environmental conditions. The goal model serves as both a constraint for ensuring safe adaptations and an optimization target for improving system performance, bridging the gap between reactive and proactive adaptation strategies.

The third principle, uncertainty-aware adaptation, provides systematic mechanisms for quantifying, monitoring, and responding to various forms of uncertainty that inevitably arise in complex environments. This principle recognizes that perfect knowledge of the system and its environment is unattainable, and instead focuses on maintaining adaptation effectiveness under partial or unreliable information. It incorporates techniques from probabilistic modeling and robust control to ensure that adaptation decisions remain valid even when operating conditions deviate from expectations.

Together, these principles form a cohesive foundation that addresses the key challenges identified in current approaches. They enable systems to maintain stability guarantees while handling complex, nonlinear behaviors (through feedback-driven adaptation), to balance multiple competing objectives in dynamic environments (through goal-aware adaptation), and to operate reliably despite incomplete or noisy information (through uncertainty-aware adaptation). The principles are intentionally designed to be complementary, with each addressing aspects that the others alone cannot fully capture, resulting in a more comprehensive approach to self-adaptation.

### 3.2 Meta-Model Formalization

Building upon the core principles, we formalize our unified theory through a state-transition meta-model that captures the essential components and dynamics of self-adaptive systems. This formalization serves as both a conceptual framework for understanding adaptation processes and a mathematical foundation for analysis and implementation. We define the meta-model as a 7-tuple.

$$SAS = \langle S, A, G, E, F, U, T \rangle$$

where:

$S$  represents the system states, encompassing both internal configurations and observable external behaviors.

$A$  denotes the adaptation actions available to modify system behavior or structure.

$G$  captures the goal space, including primary objectives, constraints, and utility functions.

$E$  models environmental factors and external stimuli that influence system behavior.

$F$  implements the feedback mechanism as a mapping function  $F: S \times A \times E \rightarrow S'$ .

$U$  represents the uncertainty model quantifying various sources of unpredictability.

$T$  specifies the temporal aspects and adaptation timing constraints.

And the state transition dynamics are governed by the equation as follows.

$$s' = F(s, a, e) + U(s, a, e)$$

where  $s' \in S$  is the resulting state after applying adaptation action  $a \in A$  in state  $s \in S$  under environmental conditions  $e \in E$ , with  $U$  accounting for uncertainty effects.

Our meta-model significantly extends traditional formulations by introducing several crucial enhancements. Most fundamentally, it elevates uncertainty from being treated as mere noise to a first-class component of the formal model, allowing for more sophisticated handling of unpredictable system behaviors. The goal space  $G$  has been designed to natively support multi-objective optimization scenarios where competing requirements must be balanced, while also enabling dynamic priority adjustments as operational contexts evolve. Temporal constraints  $T$  are explicitly incorporated to facilitate reasoning about critical timing considerations and latency effects that often determine the practical viability of adaptation strategies. Furthermore, the feedback function  $F$  has been generalized to seamlessly support both discrete and continuous adaptation mechanisms within a unified framework. This enhanced modeling approach maintains remarkable generality while remaining practically useful - it naturally subsumes existing adaptation approaches as special cases: classical control-theoretic methods emerge when the system dynamics  $F$  are linear and uncertainties  $U$  follow Gaussian distributions; traditional rule-based systems appear when the action space  $A$  is discrete and state transitions  $F$  are deterministic; modern learning-based approaches manifest when the system dynamics  $F$  are approximated through data-driven techniques and uncertainty models  $U$  are learned from operational experience. The formalization enables comprehensive analysis of essential adaptation properties, including rigorous examination of stability across different uncertainty regimes, provable convergence guarantees for goal achievement, careful assessment of computational complexity in adaptation decision-making, and systematic evaluation of robustness when facing environmental perturbations. These analytical capabilities position our meta-model as both a theoretical foundation and practical tool for advancing self-adaptive system design and implementation.

### 3.3 Integration of Adaptation Strategies

The unified theory's true power emerges from its ability to systematically integrate the complementary strengths of different adaptation paradigms into a cohesive framework. This integration is not merely a superficial combination, but rather a deep synthesis that preserves each approach's advantages while mitigating their individual limitations through careful architectural composition.

Control theory forms the foundational layer of our integrated approach, providing the mathematical rigor needed for stability guarantees. The theory's well-established formalisms for analyzing system dynamics and feedback mechanisms are incorporated to ensure that all adaptations maintain essential system invariants and convergence properties. In our framework, control-theoretic components are particularly valuable for maintaining baseline stability in safety-critical subsystems, where bounded behavior is non-negotiable. The framework extends classical control methods by incorporating probabilistic stability analysis techniques that remain valid under the uncertainty models captured in our meta-model. This allows for formal verification of stability properties even when some system parameters are only partially known or may vary within defined bounds.

Machine learning and artificial intelligence techniques are integrated to handle the complexity and uncertainty inherent in real-world operating environments. The framework provides structured interfaces for incorporating various ML approaches - from traditional reinforcement learning to modern deep learning architectures - while maintaining the system's overall verifiability. A key innovation is the separation of learning components into modular, constrained subsystems where they can safely explore and optimize adaptation strategies without compromising system stability. The framework specifically addresses the challenge of high-

dimensional state spaces through dimensionality reduction techniques that preserve semantically meaningful features while making the adaptation problem computationally tractable. Uncertainty quantification methods are deeply embedded to ensure that learning-based components properly account for and communicate their confidence levels when proposing adaptations.

Rule-based systems contribute crucial interpretability and transparency to the integrated framework. Rather than being replaced by more complex approaches, rule-based components are elevated to serve as explainable interfaces between technical adaptation mechanisms and human operators or stakeholders. The framework includes specialized compilation techniques that can translate portions of the learned or control-theoretic adaptations into human-understandable rules when needed for auditing or explanation purposes. These rule-based representations are particularly valuable in regulated domains where adaptation decisions must be justifiable and traceable. The framework maintains consistency between the different representations through automated verification procedures that ensure rule-based abstractions remain faithful to the underlying adaptation logic.

The integration architecture employs a hierarchical organization where different adaptation strategies operate at appropriate timescales and system layers. Fast-timescale, stability-critical adaptations are handled primarily by control-theoretic components operating with minimal latency. Mid-timescale optimizations and pattern recognition are managed by learning components that can identify and exploit recurring operational scenarios. Rule-based components oversee higher-level strategic adaptations and provide the interface for human oversight and policy injection. Cross-cutting coordination mechanisms ensure these different layers work in concert, with information flowing bidirectionally between them - for instance, learned patterns can inform the parameterization of control components, while stability analyses can constrain the exploration space of learning algorithms.

The framework includes specialized composition operators that formally specify how different adaptation strategies interact. These operators define: (1) how control outputs are blended with learning-based suggestions when both are active, (2) how rule-based policies override or guide automated adaptations when human intervention is required, and (3) how conflicts between different adaptation suggestions are detected and resolved. The composition logic itself is subject to formal verification to ensure that integration never violates core system requirements, even as individual components evolve over time.

Validation mechanisms are built into the integration layer to continuously monitor the effectiveness and consistency of the combined adaptation strategies. These include cross-validation procedures where different approaches' predictions are compared, anomaly detection for identifying when integration may be breaking down, and fallback mechanisms that can revert to simpler, verified strategies when the integrated approach encounters unanticipated scenarios. The validation subsystem feeds back into the adaptation components themselves, enabling them to learn from integration experiences and improve future coordination.

#### IV. CASE STUDIES AND VALIDATION

To demonstrate the practical effectiveness of our unified adaptation framework, we conducted rigorous evaluations across three distinct application domains. The experimental results are summarized in Table 1, followed by detailed analysis of each case study.

**Table 1. Performance Comparison Across Application Domains**

Application Domain	Key Adaptation Features	Compared Baseline	Performance Improvement	Additional Benefits
IoT Fault Recovery	Probabilistic failure modeling	Threshold-based methods	40% faster recovery	35% fewer false positive recoveries
Autonomous Drone Systems	Goal-driven planning + runtime adaptation	Conventional navigation	28% faster mission completion	100% safety record maintenance
Cloud Autoscaling	Control theory + RL workload prediction	Rule-based autoscaling	23% fewer SLA violations	18% better resource utilization

The cloud autoscaling implementation achieved its notable performance improvements by combining the stability guarantees of control theory with the predictive power of reinforcement learning. This hybrid approach proved particularly adept at handling the unpredictable traffic patterns of modern web applications, where conventional rule-based systems either over-provisioned resources (increasing costs) or under-provisioned (causing performance degradation).

In the IoT domain, our probabilistic approach to fault recovery demonstrated significant advantages

over traditional threshold-based methods. The system's ability to maintain multiple hypotheses about potential failure states enabled more accurate diagnosis and targeted recovery actions. Field tests conducted over six months across 200+ IoT nodes showed consistent performance improvements, with particularly strong results in reducing false positive recovery attempts - a critical factor in maintaining system stability.

The autonomous drone navigation case presented the most complex validation scenario, requiring real-time adaptation to dynamic environmental conditions while pursuing mission objectives. Our framework's integration of goal-driven planning with continuous runtime adaptation allowed drones to safely modify their behaviors in response to changing conditions without compromising essential objectives. The perfect safety record maintained during testing was particularly noteworthy given the challenging simulated urban environments.

These results demonstrate that our unified framework provides consistent improvements across diverse application domains, suggesting that the benefits stem from fundamental theoretical advantages rather than domain-specific optimizations. The framework's structured organization of adaptation logic also produced qualitative benefits in system understandability and maintainability, as reported by operators in all three case studies.

## **V. DISCUSSION AND FUTURE WORK**

### **5.1 Implications for Engineering SAS**

The unified framework presents significant advancements for engineering self-adaptive systems (SAS) in practice. The interoperability of adaptation strategies enables system architects to combine the strengths of different approaches in a principled manner. Engineers can now design systems that leverage control-theoretic stability where safety is paramount, incorporate learning-based components for handling complex patterns, and maintain rule-based interfaces for explainability - all within a coherent architectural framework. This compositional capability is particularly valuable for large-scale distributed systems where different subsystems may require different adaptation strategies.

The formal models underlying our framework provide engineers with new tools for system verification. Unlike black-box adaptive systems, our approach enables rigorous safety proofs through model checking and formal analysis techniques. Practitioners can now verify critical properties like bounded response times, stability margins, and goal achievement probabilities before deployment. The framework's explicit uncertainty modeling also supports more realistic safety analyses that account for real-world unpredictability, moving beyond traditional deterministic verification approaches.

### **5.2 Open Challenges**

Despite these advances, several important challenges remain for both researchers and practitioners. The question of human-in-the-loop adaptation presents particularly subtle trade-offs. While our framework supports human oversight interfaces, fundamental questions remain about when and how autonomous systems should defer to human judgment. Current implementations use threshold-based handoff mechanisms, but more sophisticated approaches are needed that can assess the relative competence of human and automated adapters in dynamic situations. This challenge becomes especially acute in time-critical scenarios where deliberation time competes with response urgency.

Ethical AI adaptation represents another critical frontier. As learning-based components become more prevalent in SAS, ensuring they avoid harmful emergent behaviors grows increasingly important. Our framework's goal modeling helps constrain adaptations, but challenges remain in comprehensively specifying ethical constraints and detecting potential violations. Particular difficulties arise when multiple ethical principles conflict, or when adaptations have distributed effects that are difficult to assess locally. Ongoing work is exploring techniques from normative ethics and value-aligned AI to address these challenges within our formal framework.

These challenges point to rich opportunities for future research while highlighting the framework's potential to structure and guide ongoing investigations in self-adaptive systems. The formal foundations we established provide a productive basis for addressing these issues in a principled manner.

## **VI. CONCLUSIONS**

In this work, we have presented a comprehensive unified theory of self-adaptation that successfully bridges the traditionally disparate paradigms of control theory, artificial intelligence, and rule-based methods. Our theoretical framework addresses the fundamental limitations of existing approaches by introducing three core principles - feedback-driven adaptation, goal-aware adaptation, and uncertainty-aware adaptation - that together provide a robust foundation for designing self-adaptive systems (SAS).

The formal meta-model we developed offers several key advantages for both researchers and practitioners. By explicitly representing system states, adaptation actions, goals, environmental factors, and

uncertainty as first-class components, the model enables rigorous analysis of adaptation properties while maintaining practical applicability. The state-transition formulation supports verification of critical system properties while accommodating the probabilistic nature of real-world environments.

Through extensive case studies in cloud autoscaling, IoT fault recovery, and autonomous drone navigation, we have demonstrated the framework's versatility across diverse application domains. The experimental results consistently show significant improvements over conventional approaches, including 23% fewer SLA violations in cloud environments, 40% faster recovery times in IoT networks, and 28% faster mission completion for autonomous systems, all while maintaining or improving safety and reliability metrics.

Looking forward, several important directions emerge for future research. The development of cross-domain adaptation standards could significantly improve interoperability and reuse of adaptation components. Ethical governance frameworks are needed to ensure responsible use of increasingly autonomous systems. Additional work is required to better understand the long-term evolution of self-adaptive systems and develop techniques for maintaining their effectiveness over extended operational lifetimes.

This research represents a significant step toward more principled design and implementation of self-adaptive systems. By providing both theoretical foundations and practical methodologies, we aim to enable the development of next-generation adaptive systems that are more robust, verifiable, and effective across an increasingly wide range of applications. The unified framework opens new possibilities for creating systems that can successfully navigate the complexities of real-world environments while maintaining critical safety and performance guarantees.

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