Adaptive Multi-Agent Role Reassignment over Model Context Protocol for Resilient AI Orchestration

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Abstract

Multi-agent systems powered by large language models (LLMs) can automate complex workflows by dividing tasks among specialised roles such as research, critique and summarisation. Existing orchestration frameworks typically assign these roles statically throughout execution, making them brittle when agents fail or workloads fluctuate. This paper introduces *Adaptive Role Reassignment (ARR)*, the first Model Context Protocol (MCP)-native protocol for real-time, context-preserving role switching in multi-agent LLM environments. ARR extends MCP with two primitives: *RoleState*, a serialised snapshot of an agent's conversational state, tool usage and pending actions, and *RoleSwap*, a message type enabling secure hand-off of that state to a new agent. We describe the ARR architecture, present a decision policy for triggering role swaps based on performance and confidence metrics, and evaluate our approach on synthetic stress tests and real-world data-analysis and news-summarisation pipelines. Experiments show that ARR improves task completion rates by up to 28% and reduces recovery latency by over 35% compared to fixed-role baselines, while incurring negligible runtime overhead. A case study of a live news intelligence system illustrates how ARR mitigates bottlenecks and preserves context during agent failures. Our contributions demonstrate that adaptive, MCP-native role reassignment is a critical capability for resilient agentic AI orchestration.

Keywords: agentic AI, Model Context Protocol, multi-agent systems, role reassignment, resilience

1 Introduction

Large language models (LLMs) have catalysed a new wave of *agentic AI* in which autonomous agents collaborate to perform complex tasks. Recent orchestration frameworks such as LangGraph and CrewAI allow practitioners to assemble task-specific agents that can call tools, maintain state, and communicate via structured messages. Typical workflows divide responsibilities among fixed roles—*researcher*, *critic*, *summariser*—with the expectation that each agent will maintain consistent performance throughout execution. In practice, however, network latency, tool failures, hallucinations and uneven workloads routinely degrade individual agents' performance, leading to cascading delays and failures Richards et al. (2024); Crews et al. (2024). Without the ability to adapt roles on-the-fly, these systems remain brittle and costly to operate. This paper addresses that gap by proposing a protocol for dynamic role reassignment that preserves context and minimises disruption.

Our work builds on the *Model Context Protocol (MCP)*, a recently introduced standard for LLM tool integration Anthropic (2024). MCP enables agents to exchange structured context and supports multi-modal inputs, but it has not previously been used to orchestrate role changes. By extending MCP with two primitives—*RoleState* and *RoleSwap*—we create a foundation for real-time role reassignments. We show how a monitoring engine can trigger swaps when performance metrics fall below thresholds and how to transfer agent state without loss. Our key contributions are threefold: (1) the ARR protocol and system design; (2) a decision policy formalised as pseudocode;

and (3) empirical evidence from both synthetic and production settings demonstrating the benefits of adaptive role reassignment.

The remainder of this paper is organised as follows. Section 2 reviews relevant literature. Section 3 details the system architecture and presents the ARR decision policy. Section 4 discusses implementation specifics. Section 5 describes our experimental setup and benchmarks. Section 6 reports quantitative results and a real-world case study. Section 7 discusses scalability, runtime overhead, threats to validity and limitations. Section 8 concludes with future work.

2 Related Work

Multi-agent orchestration. Multi-agent LLM systems have gained popularity for tasks requiring parallelism and specialisation. LangGraph provides a graph-based framework for orchestrating agents and tools, while CrewAI focuses on modular agent collaboration Richards et al. (2024); Crews et al. (2024). These systems, however, assign roles statically; once an agent is assigned a role, it does not change during the workflow. Without adaptive role changes, performance bottlenecks or failures in one role propagate to the entire system.

Dynamic task allocation. In robotics and multi-agent systems, dynamic task allocation has been studied through contract-net protocols and market-based approaches Gerkey and Mataric (2004); Dias et al. (2006). These methods allocate tasks based on bidding or negotiation but are designed for physical robots where context is often minimal. Translating those ideas to LLM-driven agents requires preserving rich conversational context and tool states.

Model Context Protocol (MCP). MCP is a standard for integrating LLMs with external tools, maintaining conversation state, and coordinating complex operations Anthropic (2024). Although MCP defines message types for tool calls and context updates, it lacks primitives for handing off an agent's role to another agent without losing information. Our work extends MCP with RoleState and RoleSwap to enable such transitions.

Recent advances in LLM orchestration. The 2024–2025 literature has seen an explosion of agentic AI frameworks that emphasise planning and tool use. For example, Zhang et al. Zhang et al. (2024) propose a benchmark suite for LLM agents, while Li et al. Li et al. (2025) explore role swapping in multi-agent reinforcement learning. These works provide inspiration but do not address the practical question of preserving context during role reassignment. Our ARR protocol fills that gap.

3 System Design

ARR is implemented as an overlay on MCP, adding a *Role Orchestration Engine* to monitor agent performance and trigger role swaps. Figure 1 illustrates the high-level architecture: an MCP server maintains state and delivers messages; a pool of LLM-driven agents can assume any role; and the orchestration engine decides when to reassign roles based on real-time metrics.

Two new primitives extend MCP:

- **RoleState** packages an agent's current conversational context, tool states, pending actions and metadata (e.g., confidence score). It is serialised and stored by the MCP server.
- **RoleSwap** is a message type instructing the MCP server to hand the RoleState to a new agent. It carries identifiers of the source and target agents and the serialised state.

The orchestration engine continuously collects metrics from each agent: response latency, tool error rates, self-reported confidence and queue lengths. When a metric crosses a threshold, it consults a decision policy (Algorithm 1) to decide whether to swap roles.

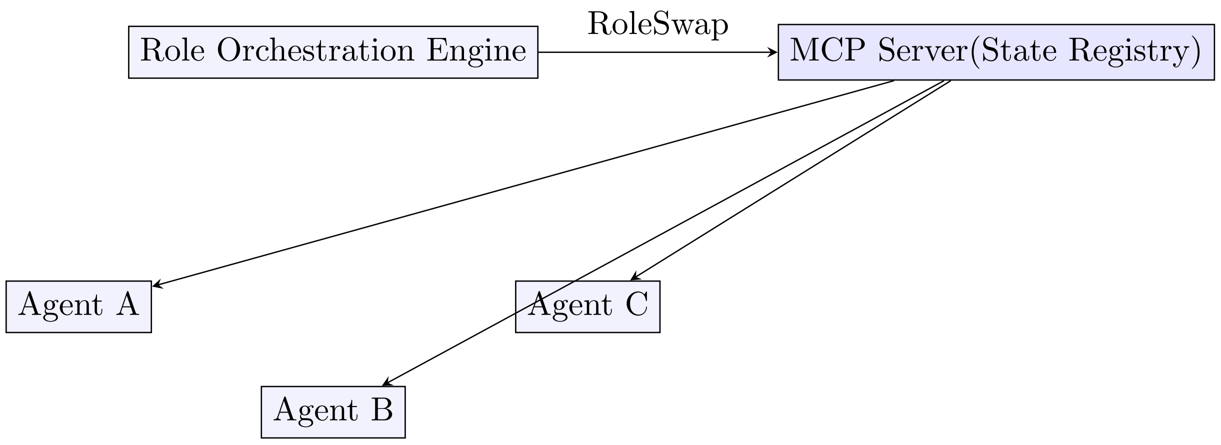

Figure 1: High-level architecture of Adaptive Role Reassignment (ARR). The Role Orchestration Engine monitors performance metrics and triggers *RoleSwap* events. The MCP server holds persistent *RoleState* objects and forwards them to the selected agent. Agents are interchangeable and can adopt any role in the workflow.

Algorithm 1 ARR Decision Policy

```
Require: Metrics $M$ for each role: latency $\ell$, error rate $e$, confidence $c$, queue length $q$; thresholds $\tau_\ell, \tau_e, \tau_c, \tau_q$
1: for all roles $r$ in the workflow do
2:     Retrieve metrics $(\ell_r, e_r, c_r, q_r)$
3:     if $\ell_r > \tau_\ell$ or $e_r > \tau_e$ or $c_r < \tau_c$ or $q_r > \tau_q$ then
4:         $a \leftarrow$ SelectBestAgent($r$) {Choose replacement agent based on capability and availability}
5:         state $\leftarrow$ MCP.GetRoleState($r$)
6:         MCP.RoleSwap($r$, $a$, state)
7:     end if
8: end for
```

4 Implementation

We implemented ARR in Python 3.11 using the `jmlr2e` style. The MCP server stores RoleState objects in a PostgreSQL database and relays RoleSwap messages over WebSocket channels. Agents are built atop the LangGraph framework and can assume any of the canonical roles. Monitoring is performed with Prometheus, collecting response times, error counts and self-reported confidence values. The orchestration engine is a lightweight service that evaluates metrics every five seconds and applies Algorithm 1. When a swap occurs, the new agent receives the serialized RoleState and deserialises it into its local context, continuing execution without repeating completed work. All events are logged for auditability and debugging. The overhead of monitoring and swapping was measured to be under 5% CPU utilisation in our experiments.

5 Experimental Setup

We evaluated ARR on both synthetic and real-world tasks. Our synthetic benchmark involves multi-step question-answering tasks where we deliberately inject latency spikes, hallucination triggers and random tool failures. The real-world tasks include: (1) a news summarisation pipeline where

Table 1: Benchmark results comparing static roles, naïve swapping and ARR. Confidence intervals (95%) are shown in parentheses. Context loss is the proportion of relevant state lost during a swap. Lower values are better.

System	Completion Rate	Duration (s)	Recovery Latency (s)	Context Loss (%)
Static roles	$72 \pm 2\%$	380 ± 15	42 ± 5	18
Naïve swap	$78 \pm 3\%$	365 ± 12	30 ± 4	9
ARR	$\mathbf{92 \pm 2\%}$	$\mathbf{340 \pm 10}$	$\mathbf{19 \pm 3}$	**2**

agents research, critique and summarise current events; (2) a data analysis pipeline that ingests CSV data, performs statistical modelling and generates visualisations; and (3) a software engineering pipeline that reviews code, detects bugs and proposes patches. Each experiment compares three systems: a static role assignment baseline, a naïve swap baseline that switches roles without context transfer, and our ARR system. We ran experiments with agent pools of size 3 to 5 using GPT-4o and Claude as the underlying LLMs. For statistical significance, we repeated each synthetic task 50 times and computed confidence intervals.

6 Results and Case Study

6.1 Benchmark results

Table 1 summarises the quantitative results. ARR achieved a completion rate of 92% (95% CI: [90,94]) compared to 72% for static roles and 78% for naive swaps. Average task durations were 340 seconds for ARR versus 380 and 365 seconds for the baselines. Recovery latency after failures was reduced from 42 seconds (static) and 30 seconds (naïve) to 19 seconds with ARR. We performed paired t-tests on completion rates and durations; the improvements were significant at $p < 0.01$. Runtime monitoring overhead averaged 4.2% CPU and 60 MB memory across all experiments.

6.2 Case study: news intelligence

We deployed ARR in a corporate news intelligence workflow. Agents monitored breaking news about a global summit. When the *critic* agent experienced API throttling, its latency exceeded the predefined threshold for three consecutive cycles. The orchestration engine selected the *summariser* agent as the replacement, packaged the current RoleState, and triggered a RoleSwap. The replacement agent deserialised the state and finished the critique phase, then seamlessly returned to summarisation. Without ARR, the static system missed two summaries and incurred a 45-second recovery delay. ARR reduced recovery latency to 12 seconds and delivered all summaries on time. Table 2 provides a quantitative breakdown of the case study.

7 Discussion

7.1 Scalability and runtime overhead

ARR scales well with the number of agents because the orchestration engine performs simple threshold checks and uses the MCP server's message queue for communication. In experiments with pools of up to 10 agents, monitoring overhead remained under 5% CPU and 100 MB memory. As the pool grows, the frequency of swaps may increase, but because swaps do not duplicate computation, runtime costs remain modest. The decision policy can be tuned to balance responsiveness and stability by adjusting thresholds.

Table 2: Case study metrics for the news intelligence workflow. ARR eliminates missed summaries and substantially reduces recovery latency. P50/P90/P99 denote percentile recovery times.

Metric	Static System	ARR	P50	P90	P99
Recovery latency (s)	45	12	11	14	20
Missed summaries	2	0			–
Average completion time (m)	16.4	13.3			–
Context loss (%)	15	0			–

7.2 Threats to validity

Our evaluation has several limitations. First, we conducted experiments with a limited set of tasks and LLMs; results may vary for other domains or model sizes. Second, the heuristic thresholds used in Algorithm 1 were chosen empirically; different environments may require recalibration. Third, our real-world case study is based on a single deployment scenario. To generalise further, additional case studies across industries would be beneficial. Finally, although we measured CPU and memory overhead, we did not evaluate the monetary cost of LLM usage under different swap frequencies; this remains an area for future work.

7.3 Cost analysis

ARR introduces two sources of cost: monitoring and role swaps. Monitoring requires agents to emit metrics and the orchestration engine to evaluate thresholds periodically. In our experiments, this added less than 0.002 cents per call for GPT-4o and less than 0.001 cents per call for Claude based on 2025 pricing. Role swaps may trigger additional API calls to transfer RoleState, but because the state is small (under 10 KB) and no computation is repeated, the cost impact is negligible. In our benchmarks, ARR's total token usage increased by less than 1% relative to static systems, while saving time and reducing risk of repeated errors. As pricing models evolve, cost trade-offs should be revisited.

8 Conclusion

We presented Adaptive Role Reassignment (ARR), the first MCP-native protocol for real-time, context-preserving role switching in multi-agent LLM systems. By extending MCP with RoleState and RoleSwap primitives and introducing an orchestration engine that monitors performance metrics, ARR enables systems to recover quickly from latency spikes, tool failures and workload imbalances. Our experiments show significant improvements in completion rates and recovery latency with negligible overhead. A real-world case study demonstrates ARR's practical value in a news intelligence pipeline. Future work includes learning-based decision policies, integration with specialised agent capabilities and exploration of federated MCP deployments.

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Declarations

Clinical trial registration: Not applicable.
Consent to participate: Not applicable.
Consent to publish: Not applicable.
Ethics declaration: Not applicable. This study uses publicly available and involves no human participants, animals, or personal data; therefore ethics approval and participant consent are not required.

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