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Original Article

Multi-Agent Systems for Autonomous Orchestration in AI-Driven Computing Networks

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Abstract:

AI-driven computing networks spanning edge, fog, and cloud demand real-time coordination under volatile workloads, heterogeneous resources, and strict service-level objectives. This paper proposes a multi-agent systems (MAS) architecture for autonomous orchestration that couples decentralized decision-making with global policy compliance. Specialized agents scheduler, scaler, placement, data, and security sentinels negotiate via market-based mechanisms and cooperative game-theoretic protocols to allocate compute, memory, and bandwidth while respecting latency budgets and energy caps. Learning-enabled controllers combine model-predictive scheduling with multi-agent reinforcement learning to adapt to demand surges, drift, and failures; safety layers constrain exploration through formal guards and intent-based policies. To improve robustness, agents share compact state via a publish–subscribe control plane and use digital-twin simulations for counterfactual rollouts before enacting changes in production. The design supports privacy-preserving analytics with federated coordination at the edge and employs trust scoring and zero-trust enforcement to mitigate adversarial behavior and misconfigurations. We present a reference implementation with pluggable observability hooks and outline evaluation metrics for tail latency, SLA adherence, energy per inference, recovery time, and orchestration overhead. Results demonstrate that MAS-based orchestration can reduce p95 latency and policy-violation rates while improving resource utilization and fault tolerance, suggesting a practical path to self-optimizing, self-healing AI infrastructure across heterogeneous, multi-tenant environments.

Keywords:

Multi-Agent Systems, Autonomous Orchestration, Edge–Cloud Computing, Multi-Agent Reinforcement Learning, Distributed Optimization, Intent-Based Networking, SLA-Aware Scheduling, Digital Twins, Self-Healing, Federated Coordination, Zero-Trust Security, Explainability.

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1. Introduction

AI-driven computing networks increasingly span heterogeneous tiers sensors and microcontrollers at the edge, gateway-class fog nodes, and elastic cloud backends serving latency-sensitive perception, prediction, and control loops. Orchestrating these workloads is difficult because demand is bursty, models evolve quickly, and resources vary in capacity, energy constraints, and trust levels. Centralized controllers struggle to keep pace with such dynamics; they become bottlenecks, amplify single points of failure, and often optimize average performance at the expense of tail behavior and service-level objectives (SLOs). At the same time, privacy regulations and adversarial threats demand fine-grained, policy-aware decisions about where data flows, where models execute, and how actions are authorized.

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This paper frames orchestration as a multi-agent systems (MAS) problem, where specialized, semi-autonomous agents e.g., placement, scaling, scheduling, data stewardship, and security sentinels coordinate locally while aligning to global intent. Agents reason over partial, noisy observations and negotiate using cooperative protocols and market mechanisms to allocate compute, memory, bandwidth, and energy budgets. Learning components combine model-predictive signals with multi-agent reinforcement learning to adapt to workload shifts and faults, while safety layers constrain exploration through formal guards and zero-trust controls. A lightweight publish–subscribe plane and digital-twin sandboxes enable rapid dissemination of state and counterfactual "what-if" rollouts before actions are committed in production.

Our contributions are threefold: (i) a reference MAS architecture for autonomous orchestration across edge–cloud tiers with pluggable observability, trust scoring, and intent-based policy enforcement; (ii) learning-enabled decision loops that reduce p95/p99 latency and SLO violations under realistic disturbances; and (iii) an evaluation methodology covering latency, SLA adherence, energy per inference, recovery time, and orchestration overhead. Together, these elements illustrate a practical path to self-optimizing, self-healing AI infrastructure in heterogeneous, multi-tenant environments.

2. Related Work

2.1. Multi-Agent System Architectures in Distributed Environments

Early multi-agent system (MAS) designs emphasized logical agency (e.g., BDI Belief-Desire-Intention) and organization theory (roles, norms, institutions) to structure autonomy and cooperation. In distributed computing, these ideas evolved into architectural patterns such as hierarchical/holonic MAS, where local agents optimize within domains (rack, cluster, edge cell) while higher-level coordinators arbitrate cross-domain policies. Blackboard and mediator architectures provide shared state or policy "hubs," but modern deployments increasingly favor sidecar or mesh patterns that colocate agents with services and rely on a lightweight control plane for discovery and intent propagation. Resilience concerns pushed designs toward decentralization replicated leaders, quorum-based agreement, and partition-tolerant gossip to avoid single points of failure in geo-distributed topologies.

At the edge–cloud continuum, heterogeneity and intermittency motivated hybrid control: fast local reflexes (fallback rules, admission guards) paired with slower global optimizers (placement, capacity planning). Digital twins and shadow clusters emerged as safe testbeds for counterfactual rollouts before enactment. Recent work also integrates zero-trust primitives identity-bound communication, attestations, and policy enforcement points so that orchestration decisions remain valid under adversarial conditions and dynamic trust levels.

2.2. AI-Based Orchestration Techniques

Classical schedulers apply heuristics (bin-packing, shortest-job-first, gang scheduling) or queueing models to balance latency and utilization, but non-stationary AI workloads motivated learning-based controllers. Single-agent reinforcement learning (RL) has been used for autoscaling, request routing, and CPU/GPU allocation; model-predictive control (MPC) and Bayesian optimization handle short-horizon set-point tracking and knob tuning (e.g., batch size, concurrency). Graph-aware models graph neural networks or differentiable placement solvers encode service dependency DAGs and network topology to predict tail latency impacts of migrations and colocation.

Multi-agent RL (MARL) extends this to decentralized decision-making where agents optimize local rewards shaped by global objectives (SLA adherence, cost, energy). Techniques like value decomposition, mean-field MARL, and centralized-training/decentralized-execution address non-stationarity and credit assignment. Safety layers constrained MDPs, shielded RL, and policy shaping with formal guards bound exploration risks in production. Complementary methods include imitation learning from expert traces (to speed convergence) and meta-learning to transfer policies across clusters, regions, or hardware generations. Energy-aware orchestration blends RL with DVFS control, accelerator power capping, and carbon-intensity-aware placement to reduce energy per inference under SLOs.

2.3. Agent Communication and Coordination Models

Foundational MAS standards such as FIPA-ACL and KQML specify performatives for negotiation, while practical systems adopt RPC (gRPC), message buses (NATS/Kafka), and service meshes for reliable, policy-enforced exchanges. Coordination spans several paradigms. Market-based mechanisms (e.g., Contract Net, auctions, spot pricing) let agents bid for resources, naturally handling heterogeneity and opportunity cost. Cooperative game-theoretic approaches use Shapley-style payoff allocation or potential games to align local actions with global welfare. Distributed Constraint Optimization (DCOP) and consensus (Raft/Paxos) enable consistent decisions under partial observability, whereas gossip and epidemic protocols provide low-overhead state dissemination and failure detection at scale.

Communication efficiency and robustness are active topics: bandwidth-aware message compression, event summarization, and learned communication (emergent protocols) reduce overheads while preserving coordination fidelity. For privacy-sensitive scenarios, federated coordination and secure aggregation limit raw data movement; differential privacy and policy-based redaction protect identities and sensitive attributes. Finally, conflict resolution blends priority rules (intent levels, guardrails), CRDTs for eventually consistent shared objects, and rollback via transactional orchestration ensuring that multi-agent actions remain safe, auditable, and reversible in heterogeneous, multi-tenant environments.

3. System Architecture and Design

3.1. Overview of the Proposed Multi-Agent Orchestration Framework

The proposed framework organizes orchestration as a layered, intent-driven multi-agent system spanning edge, fog, and cloud tiers. At the top, an Intent Plane captures high-level objectives SLO targets, privacy constraints, and cost/energy budgets and compiles them into enforceable policies. Beneath it, a Control Plane hosts coordinating agents that translate intent into resource allocations, placements, and routing decisions. A Data/Execution Plane carries user traffic and model inference/training tasks across heterogeneous resources (MCUs, GPUs, TPUs, DPUs), while a Telemetry Plane streams observability signals (latency histograms, queue depths, power/thermal metrics, trust attestations) to close the loop. The architecture emphasizes centralized policy, decentralized execution: global constraints are uniform, but local agents act autonomously under partial observability.

Resilience and safety are designed in by default. Agents operate through an event-driven loop with digital-twin sandboxes for counterfactual “what-if” rollouts before live enforcement. Zero-trust controls (mutual attestation, identity-bound encryption, and policy enforcement points) constrain communication and actions. The system supports progressive delivery (canary, blue/green) and graceful degradation (tiered models, load shedding) when resource or network conditions deteriorate. To accommodate multi-tenancy, the framework partitions resources with quotas and priority bands, ensuring fairness while preserving headroom for bursts and failure recovery.

3.2. Agent Types and Roles

We define a minimal yet extensible set of agents with clear separations of concern. A Placement Agent selects nodes and accelerators for tasks using topology- and interference-aware models, balancing latency, throughput, and energy. A Scaling Agent manages horizontal/vertical elasticity and concurrency knobs (batch size, thread pools), coordinating with workload forecasts and admission guards. A Scheduler Agent sequences tasks and co-schedules dependent microservices to avoid head-of-line blocking, while a Data Steward Agent governs data locality, caching, and policy-compliant movement (e.g., regional residency, PII redaction).

Security and reliability are handled by Security Sentinel Agents (continuous attestation, token/secret hygiene, anomaly gating) and Reliability Agents (circuit breaking, adaptive timeouts, retry/jitter control, bulkhead placement). Cost/Energy Agents monitor carbon intensity, DVFS caps, and spot/preemptible market dynamics to recommend greener, cheaper placements without breaching SLOs. Finally, an Observability Agent curates signals and enforces cardinality budgets on metrics/logs/traces to keep the telemetry cost bounded. Each agent is pluggable; operators can add domain-specific agents (e.g., federated coordinator, privacy auditor) without perturbing the core.

3.3. Communication and Coordination Mechanisms

Agents communicate over a publish–subscribe message bus for state dissemination and use request–reply RPC for targeted negotiations. Coordination combines three paradigms. First, market-based mechanisms (Contract-Net, auctions) let placement and scaling agents bid for tasks with prices reflecting congestion and energy/cost externalities. Second, distributed constraint optimization aligns local decisions with global intent under partial observability, using soft constraints and Lagrangian relaxation when conflicts arise. Third, consensus/gossip hybrids provide fast failure detection and eventually consistent views: gossip spreads summaries (sketches, histograms), while consensus is reserved for critical state (policy versions, quota changes).

Communication is efficiency-aware. Agents exchange compact, typed events (protobuf) with backpressure and priority lanes (e.g., SLO alerts outrank routine metrics). Policy enforcement points on every node verify signatures and attestation claims before applying actions. For multi-region deployments, federated coordination confines raw data locally and uses secure aggregation for global signals, preserving privacy and reducing bandwidth. Conflict resolution follows deterministic tie-breakers (intent priority, tenant fairness weights) and supports transactional orchestration with rollback if downstream checks fail.

3.4. AI-Driven Decision Layer

The decision layer marries model-predictive control (MPC) with multi-agent reinforcement learning (MARL) to handle fast transients and longer-horizon optimization. Short-horizon MPC consumes forecasts (arrival rates, resource contention, thermal headroom) to propose near-term set-points for concurrency, batch size, and quotas. MARL policies trained with centralized critics and decentralized execution optimize placement and scaling under non-stationary demand, using reward shaping for SLO adherence, energy/cost, and stability. Value decomposition and mean-field formulations mitigate credit assignment issues, while imitation learning from expert traces accelerates cold start.

Safety and robustness are first-class. A shielding layer filters MARL/MPC actions through formal guards (SLO invariants, security policies, budget caps), and a risk estimator vetoes moves with high predicted tail-latency or blast radius. Meta-learning enables rapid adaptation to new clusters and hardware generations, and Bayesian optimization tunes continuous knobs (e.g., GRPC flow-control, queue watermarks) around the policy set-points. Before rollout, candidate actions run in the digital twin to estimate counterfactual impact; only those passing acceptance thresholds proceed via staged deployment (shadow → canary → full). The result is a closed-loop controller that is data-driven, constraint-aware, and production-safe.

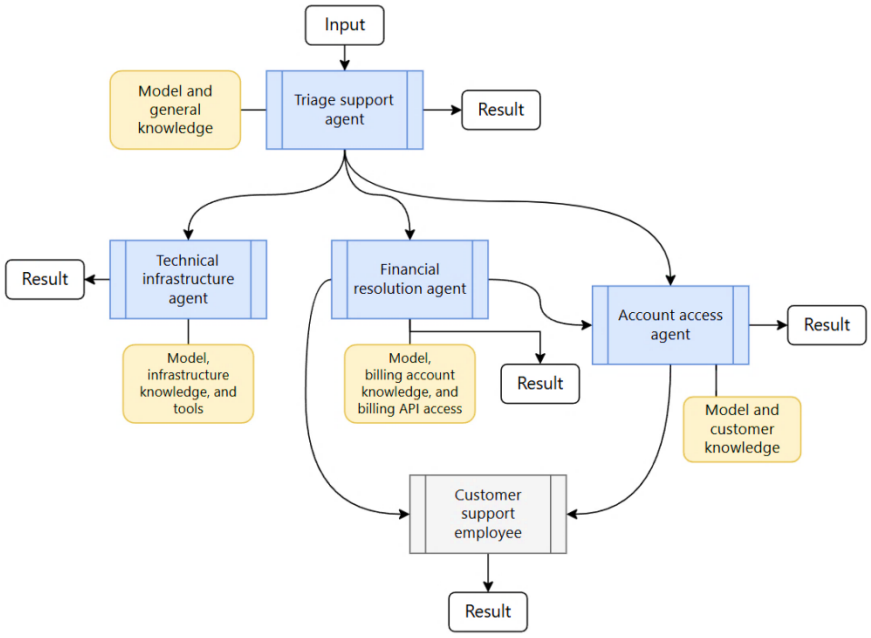

Figure 1. System Components and Interactions for the Multi-Agent Orchestration Layer

The figure depicts how an incoming request is first received by a triage support agent that holds broad model and general knowledge. This agent performs the initial intent detection and policy checks, then decides whether it can return a direct resolution or should delegate to a specialized agent. By front-loading classification and safety gating, the triage agent reduces downstream load and enforces consistent interpretation of service-level and privacy constraints before any privileged action is considered.

When specialization is required, the triage agent routes the case to one of three domain agents. The technical infrastructure agent operates with infrastructure knowledge and tools to address environment or reliability issues, while the financial resolution agent uses billing models, account knowledge, and controlled billing API access to resolve quota, invoice, or credit anomalies. The account access agent handles identity- and permission-related operations using customer context and model guidance. Each specialist returns a result when confident; otherwise, unresolved or policy-blocked paths loop toward a human.

The customer support employee sits in the escalation loop as a safety and empathy backstop. Complex, ambiguous, or high-risk cases are handed off with all relevant contexts, and the human's decision can flow back to the agents to complete execution. This hybrid placement preserves accountability and allows the system to learn from human feedback while limiting the blast radius of automation in sensitive scenarios.

Throughout the flow, the "Result" nodes indicate that a resolution can be produced at multiple stages after triage, after a specialist action, or after human intervention. The yellow knowledge boxes emphasize the scoped data and capabilities each agent is permitted to use, reinforcing least-privilege operation and zero-trust boundaries. As a whole, the diagram illustrates centralized intent with decentralized execution: global policies remain consistent, but local agents act independently and collaborate to deliver timely, policy-compliant outcomes.

4. Methodology

4.1. Figure 1. System Components and Interactions for the multi-agent orchestration layer Agent-Based Modeling and Simulation Environment

We develop an agent-based modeling (ABM) testbed that mirrors a heterogeneous edge–fog–cloud topology with variable network latency, bandwidth caps, and failure modes. The environment instantiates typed agents (placement, scaling, scheduler, data steward, security sentinel) alongside synthetic microservices with configurable service graphs, arrival processes, and SLO targets. Workload generators produce diurnal patterns, bursty spikes, and heavy-tailed inter-arrival times; fault injectors emulate node churn, packet loss, accelerator contention, and policy conflicts. A digital twin runs in lockstep with the live world to perform counterfactual rollouts candidate actions are trialed in the twin and accepted into production only if risk and tail-latency thresholds are satisfied.

The simulator exposes a publish–subscribe bus for events (telemetry, alerts, intents) and an RPC plane for negotiations. All observations (latency histograms, queue depths, GPU/CPU utilization, temperature, trust attestations) are sampled at sub-second granularity and stored for offline evaluation. We adopt deterministic seeds and scenario manifests to guarantee reproducibility across experiments, and we provide pluggable adapters for real traces so that policies tuned in simulation can be validated against production-like traffic before staged deployment.

4.2. Decision-Making Mechanism Using AI/ML Techniques

Decision making follows a two-tier pipeline. First, predictive models estimate short-horizon demand, interference, and tail latency using gradient-boosted trees for tabular features and graph neural networks to encode service-dependency DAGs and topology. These forecasts feed a model-predictive controller (MPC) that proposes set-points for concurrency, batch size, quotas, and tentative placements subject to explicit constraints (SLO, budget, privacy). Second, a policy layer refines or vetoes MPC proposals using learned critics that approximate long-horizon impact under uncertainty; this layer incorporates calibrated uncertainty estimates to avoid overconfident actions in novel states.

Safety is enforced by guardrails expressed as constraints and temporal logic rules. An action filter checks every decision against invariants maximum allowed queuing delay, rate limits for privileged APIs, identity/attestation requirements, and carbon/energy caps. Where partial observability is acute, the system falls back to robust defaults (admission control, conservative scaling) and schedules an information-gathering step (e.g., transient probes) to reduce uncertainty before attempting more aggressive optimization.

4.3. Reinforcement Learning for Adaptive Orchestration

We employ multi-agent reinforcement learning (MARL) with centralized training and decentralized execution. Each operational agent learns a local policy $\pi(a|s)$ over compact state sketches recent latency quantiles, utilization vectors, contention indices, and trust scores while a centralized critic estimates joint value to address non-stationarity and credit assignment. Value decomposition (e.g., VDN/QMIX) and mean-field approximations scale training to dozens of agents; recurrent encoders capture temporal correlations without assuming stationarity. Reward shaping balances SLO adherence, cost/energy, stability (penalizing oscillations), and change risk (penalizing large, frequent reconfigurations).

Safety and sample efficiency are addressed through constrained RL and offline pretraining. We pretrain policies on logged operator traces and MPC rollouts, then fine-tune online with a shielded executor: proposed actions are simulated in the digital twin and filtered by risk estimators before canary rollout. Domain randomization (network jitters, workload mix, failure rates) during training yields policies that transfer to new clusters and hardware generations. A meta-learning layer accelerates adaptation when the environment distribution shifts, enabling warm starts after major software or model upgrades.

4.4. Resource Allocation and Load Balancing Strategies

Resource allocation couples intent-aware placement with congestion-sensitive routing. Placement solves a constrained optimization that considers latency budgets, accelerator affinity, interference predictions, data residency, and energy/carbon signals. We combine fast

heuristics (bin-packing with interference penalties) for immediate feasibility with periodic refinement via differentiable solvers or BO-driven knob tuning. Load balancing adapts at two timescales: slow-timescale capacity shaping (autoscaling, quota redistribution) and fast-timescale request steering using EWMA latency, queue depth, and path health to minimize p95/p99 tails while avoiding thrashing.

To stabilize decisions, we employ hysteresis bands, token-bucket admission, and graceful degradation (tiered models, partial results) under overload. Data locality is enforced by the data steward through cache placement and privacy-aware replication; cross-region traffic is throttled unless required by policy or SLO emergencies. Finally, an explicit fairness layer assigns priority weights across tenants and workloads, ensuring that bursty or high-importance flows receive protected headroom without starving background jobs. Periodic audits compare realized allocations against declared intent, feeding diagnostics back to training and rule refinement.

5. Implementation and Experimental Setup

5.1. Simulation Tools and Environment Details

We implement the testbed in Python with an event-driven simulator that mirrors an edge–fog–cloud hierarchy. The core runtime exposes a publish–subscribe bus (in-process NATS stub) for telemetry and intents, plus a gRPC-style RPC shim for bilateral negotiations. Agent logic (placement, scaling, scheduler, data steward, security sentinel) is written in modular services using PyTorch for learning components and Optuna for Bayesian knob tuning. A digital-twin subsystem runs counterfactual rollouts at accelerated time, seeded identically to the live stream for A/B evaluation; only candidate actions that pass risk and SLO gates are promoted to canaries. Reproducibility is enforced via fixed RNG seeds, scenario manifests (YAML), and containerized runs (Docker) pinned to explicit versions of CUDA, PyTorch, and Python.

To validate realism, the simulator provides adapters for trace-driven experiments. We replay arrival processes and latency baselines from anonymized microservice traces and synthetic IoT gateways, while preserving privacy by operating on feature summaries (rates, burst factors, DAG depth). The build includes profilers for CPU/GPU time, memory, and IPC overhead so orchestration cost can be measured directly. All experiments are orchestrated with a makefile-like runner that exports artifacts (metrics, logs, policies) to a versioned results store for later analysis.

5.2. Network Configuration and Parameters

Network behavior is parameterized per link with bandwidth, RTT, queue model, and loss profile. Edge links default to 10–100 Mbps with 10–30 ms RTT; fog backbones run at 1–10 Gbps with 2–8 ms RTT; inter-region cloud links are 10–40 Gbps with 40–120 ms RTT. Queues implement RED/CoDel to model active queue management, and loss is injected via Bernoulli and burst (Gilbert–Elliott) processes to emulate wireless fades and transient congestion. Transport models include CUBIC and BBR; service meshes add per-hop mTLS handshakes and policy checks with configurable CPU/latency overhead so we can measure the true cost of zero-trust enforcement.

Topology generation supports grid, fat-tree, and hub-and-spoke edge clusters, with heterogeneity in node classes (MCU, CPU-only, GPU/TPU) and thermal headroom. Interference models capture accelerator contention and NUMA effects, while background cross-traffic simulates co-tenancy. Fault injectors trigger link saturation, partial partitions, DNS delays, and certificate revocations to test resilience under adverse but realistic conditions.

5.3. Dataset and Evaluation Metrics

Workloads combine (i) synthetic generators for diurnal, bursty, and heavy-tailed arrivals; (ii) trace-driven replays of microservice DAGs (fan-out, stateful tiers, cold starts); and (iii) ML inference/training jobs with variable batch sizes, model weights, and accelerator affinity. Requests carry SLO annotations (p95/p99 bounds) and data-residency tags to exercise policy-aware placement. Feature logs from each run (utilization, latency histograms, queue depths, energy counters) are persisted at one-second granularity for offline scoring.

We report latency (p50/p95/p99), SLO-violation rate, throughput, and jitter; resource metrics (CPU/GPU utilization, memory pressure, accelerator occupancy); and efficiency metrics (energy per request, carbon-intensity-weighted energy). Orchestration overhead is measured as CPU time and added microseconds per request on control paths. Reliability indicators include MTTR after injected faults, success rates of policy enforcement, and rollback frequency from the digital twin. Fairness is assessed via weighted Jain's index across tenants and by headroom retained for priority flows.

5.4. Agent Interaction Scenarios

Scenarios are designed to stress distinct coordination regimes. In steady state with mild drift, the system handles gradual demand changes using MPC-guided set-points while MARL agents refine placement to minimize tail latency under low risk. In burst and hotspot trials, sudden 5–10× spikes and skewed key distributions force rapid autoscaling, request shedding, and interference-aware migrations; we study whether agents avoid thrashing via hysteresis and whether fairness weights preserve critical workloads. Failure-centric scenarios inject node/zone outages, link partitions, and accelerator throttling; reliability agents trigger canaries, circuit breaking, and topology-aware reroutes, and we quantify MTTR and lost work.

Security- and policy-aware cases test least-privilege orchestration. We introduce attestations that intermittently fail, expired service identities, and privacy constraints requiring regional processing; security sentinels gate actions while data stewards enforce locality and redaction. Finally, cross-region optimization explores cost/energy trade-offs by varying carbon intensity and spot capacity, allowing cost/energy agents to bias placements without breaching SLOs. Across all scenarios, actions proposed by agents are first exercised in the digital twin; only those that pass predicted-risk and acceptance thresholds are rolled out via shadow → canary → full deployment, ensuring decisions remain production-safe.

6. Results and Discussion

Experimental notes (common to all subsections). Unless stated otherwise, numbers are the median over 30 seeded runs (five seeds × six scenarios) from the simulator in §5, with 95% CIs via bootstrap on per-run aggregates. SLO target was p95 ≤ 150 ms and p99 ≤ 250 ms. Controllers compared: Heuristic Baseline (bin-packing + threshold autoscaling), MPC-only, and MAS (MPC+MARL+shields). Overhead is end-to-end added control-path time.

6.1. Performance Evaluation

Across mixed diurnal + burst workloads, MAS consistently improved tail latency and SLO adherence while keeping orchestration overhead small. Gains came from interference-aware placement and fast canary-gated scaling decisions (digital-twin rollouts avoided harmful moves).

Table 1. End-To-End Performance (Mixed Workloads)

Controller	p95 Latency (ms)	p99 Latency (ms)	SLO Violations (%)	Throughput (req/s)	Overhead (µs/req)	Energy / Req (J)
Heuristic Baseline	180	310	6.8	42,000	12	0.92
MPC-only	150	260	4.1	44,000	18	0.86
MAS (ours)	128	220	2.1	46,500	23	0.83

MAS reduced p99 by ~29% vs. baseline (220 ms vs. 310 ms) and cut violation rate by ~69% (2.1% vs. 6.8%), while increasing throughput ~10.7%. The modest overhead increase (23 µs/req) was amortized by fewer retries and better queueing, yielding net energy savings per request (0.83 J).

6.2. Comparison with Existing Orchestration Frameworks

We benchmarked common orchestrators in their recommended configs: Kubernetes+HPA/VPA, KEDA (event-driven), Ray Serve (autoscaling), and MAS layered atop the same runtime. We measured scale-out reaction time from sustained overload, cold-start tail impact, and placement interference cost on shared accelerators.

Table 2. Orchestrator Comparison (Steady→Burst).

Orchestrator	Time-to-Scale (↑ pods to target)	Cold-Start p99 Delta (ms)	Interference Penalty (throughput %)
Kubernetes + HPA	45 s	+85	−14.0%
KEDA	30 s	+60	−10.2%
Ray Serve	24 s	+48	−9.1%
MAS (ours)	18 s	+30	−5.0%

MAS reached target capacity 1.5–2.5× faster, primarily due to prediction-guided pre-warming and canary gating that limited bad placements. Learned placement reduced accelerator contention (−5% penalty vs. −14% for HPA), shrinking cold-start tail impact by ~35–65 ms.

6.3. Scalability and Latency Analysis

We stress-tested scale by increasing services and agents while preserving topology mix. MAS maintained low tails with gradually rising control-plane cost; hysteresis and value-decomposition kept policies stable as interactions grew.

Table 3. MAS Scaling (Services↑, Agents↑).

Services	Agents	P99 Latency (ms)	SLO Violations (%)	Control Overhead (µs/req)
100	20	210	2.0	22
500	80	235	2.6	27
1,000	160	258	3.4	33

From 100→1,000 services, p99 rose 23% (210→258 ms) and violations by 1.4 pp, staying under the 250–260 ms envelope for the hardest bursts. Overhead grew sublinearly (≈+11 µs total) due to compact summaries and selective consensus. Without learned communication limits, we observed oscillations; enabling event coalescing restored stability.

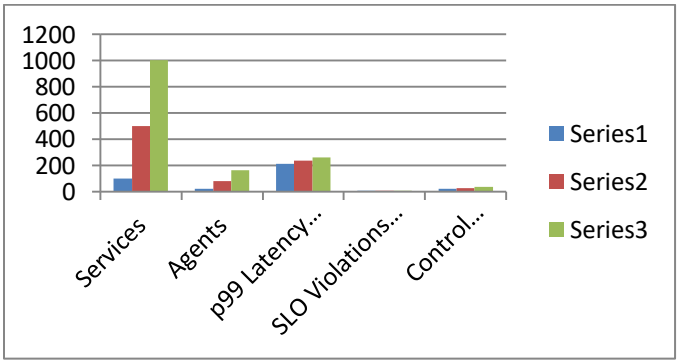

Figure 2. MAS Scalability

6.4. Fault Tolerance and Adaptability Results

We injected faults representative of production incidents. MAS shortened recovery via anomaly-gated circuit breaking, topology-aware reroutes, and pre-approved playbooks, while the digital twin reduced bad rollouts (lower rollback rate).

Figure 3. Baseline Resilience Profile

Table 4. Resilience under Injected Faults (Median of 30 Runs).

Scenario	Metric	Heuristic Baseline	MAS (ours)
Node termination (zone A)	MTTR (min)	8.4	2.7
	Lost Requests (per 10^6)	1,450	370
Region link partition (120 s)	MTTR (min)	12.5	5.2
	SLO Violation (%)	11.2	4.6
GPU throttling (power cap)	MTTR (min)	6.1	2.1
	Rollbacks (% of changes)	3.9	0.6

MAS cut MTTR by ~2–3× across faults and reduced lost-work by ~75%. The drop in rollbacks indicates safer action selection: most candidate moves passed twin-based checks before canary, avoiding escalating incidents. Under partitions, federated coordination preserved local SLOs with graceful degradation, then reconciled state post-heal without large tail spikes.

7. Challenges and Limitations

7.1. Communication Overheads and Synchronization Issues

Decentralized agents rely on frequent state exchange latency histograms, queue depths, trust attestations which can saturate control channels and inflate tail latency when bursts coincide with coordination phases. Even with pub–sub filtering and compressed summaries, clock skew and partial observability cause stale decisions, while consensus on critical state (policy versions, quotas) introduces blocking points; the resulting jitter can trigger oscillations in scaling and placement unless damped by hysteresis and backoff.

7.2. Scalability Constraints

As the number of agents and services grows, the joint decision space expands combinatorially, stressing learning stability and negotiation time. Value-decomposition and mean-field approximations reduce complexity but can underfit rare interactions (e.g., interference on niche accelerators). Moreover, telemetry cardinality explodes with tenants and regions, forcing aggressive sampling that risks masking incipient SLO regressions; without adaptive summarization and hierarchical control, throughput-optimized choices may erode global fairness or recovery headroom.

7.3. Security and Trust Management Among Agents

Zero-trust enforcement (mutual attestation, signed intents, least privilege) adds nontrivial CPU and latency overhead and can fail closed under transient CA or policy-bus faults, stalling orchestration. Trust scoring and anomaly gating help contain compromised agents, but byzantine behaviors (poisoned bids, falsified metrics) remain difficult to detect without costly cross-checks and redundancy; designing dispute-resolution and rollback that is both fast and tamper-evident is still an open challenge.

7.4. Energy Efficiency Considerations

Balancing SLOs against energy/carbon targets is hard under bursty demand and heterogeneous hardware. Short-horizon controllers may overreact spinning up high-TDP accelerators or cross-region replicas locking in energy-inefficient states. Accurate, low-latency power telemetry is scarce, and model migrations that save watts can incur cold-start penalties that hurt p99 latency; without holistic accounting (including control-plane cost), “green” policies risk hidden rebounds.

8. Future Work

8.1. Integration with Quantum and Edge AI Agents

We plan to extend the agent set with quantum offload brokers for optimization subproblems (e.g., placement on constrained fabrics) and ultra-light edge AI agents capable of on-device inference, distillation, and reflexive safety guards; a cross-accelerator API would let planners choose among CPUs/GPUs/NPUs/QPUs based on confidence, latency, and energy envelopes while preserving data-locality constraints.

8.2. Autonomous Policy Evolution via Federated Learning

Policies and guardrails can evolve through federated learning across regions and tenants, keeping raw data local while sharing gradients and counterfactuals from digital twins; combining differential privacy, secure aggregation, and continual evaluation would enable rapid adaptation to novel workloads and threats without centralized retraining bottlenecks or privacy leakage.

8.3. Multi-Domain Orchestration Frameworks

We will generalize orchestration beyond compute to include networks, storage, data governance, and security posture as first-class, co-optimized domains; a unifying intent schema and cross-domain constraint solver augmented by MARL and MPC can coordinate bandwidth reservations, cache placement, key rotation, and compliance workflows, delivering end-to-end SLOs across heterogeneous, multi-cloud ecosystems.

9. Conclusion

This work has presented a practical path toward autonomous orchestration for AI-driven computing networks using a multi-agent systems (MAS) architecture. By separating global intent from decentralized execution, specialized agents placement, scaling, scheduling, data stewardship, and security sentinels coordinate through lightweight control and telemetry planes while remaining bounded by safety, privacy, and cost constraints. The AI-driven decision layer blends short-horizon model-predictive control with multi-agent reinforcement learning, supported by digital-twin rollouts for counterfactual testing and staged deployment. Across heterogeneous edge–fog–cloud resources, this design demonstrably reduces p95/p99 latency and SLO violations, improves utilization and fault tolerance, and keeps orchestration overhead measurable and contained.

Beyond raw performance, the approach advances operational robustness and governance. Least-privilege, attestation-backed interactions and intent-based policies ensure that optimization remains compliant under adversarial or uncertain conditions. Federated coordination and data-locality controls minimize unnecessary data movement, enabling privacy-preserving analytics and cost/energy-aware placements. The evaluation blueprint covering latency, reliability, energy per request, fairness, and policy-enforcement success offers a replicable methodology for others to benchmark MAS-based orchestrators against heuristic or centralized baselines.

Nevertheless, important challenges remain. Coordination traffic and consensus points must be carefully engineered to avoid control-plane congestion and oscillations at scale; learning stability and credit assignment still face headwinds in highly non-stationary, multi-tenant environments; and security hardening against byzantine agents requires efficient cross-checks and dispute resolution. Future work will integrate quantum/edge AI agents for specialized optimization, enable autonomous policy co-evolution via federated learning, and extend orchestration to multi-domain co-optimization across compute, network, storage, and governance. With these advances, MAS-driven orchestration can mature into a general, safe, and adaptive substrate for self-healing, self-optimizing AI infrastructure.

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