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Adaptive Load Balancing in Ldoms Using Edge AI Models

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Abstract- Oracle Solaris Logical Domains (LDOMs) offer flexible, high-performance virtualization at the hardware layer, enabling fine-grained resource allocation across critical workloads. However, as enterprise infrastructures grow in complexity and scale particularly in edge and hybrid environments the need for dynamic and intelligent load balancing becomes paramount. Traditional static and reactive policies fall short in addressing modern demands marked by workload volatility, bursty usage patterns, and constrained physical resources. In this context, Edge AI models present a transformative approach to adaptive load management. This review explores how AI particularly Edge-deployed supervised, unsupervised, time-series, and reinforcement learning models can be leveraged to predict resource saturation, detect faults, and proactively manage LDOM reallocation and live migrations. Emphasis is placed on integrating AI pipelines with Solaris-native telemetry tools (kstat, vmstat, prstat) and automating control actions using the ldm command suite. Real-world case studies across telecom, financial, and healthcare sectors are analyzed to demonstrate improvements in SLA compliance, resource efficiency, and fault avoidance through AI-assisted decisions. We further address system-level integration with Oracle Ops Center, highlight governance concerns such as model explainability and override control, and explore lightweight inference frameworks suitable for constrained control domains. Challenges in data quality, model trust, and automation safety are also discussed. The review concludes by outlining future directions including federated learning, policy-aware AI agents, cross-domain telemetry fusion, and convergence with AI-Ops ecosystems. By embedding intelligence directly into the LDOM infrastructure, organizations can evolve from static resource provisioning to a self-optimizing virtualization platform—capable of continuous learning, rapid adaptation, and resilience at the edge. This shift is vital to meet the performance and operational demands of modern digital infrastructure.

Index Terms- Oracle LDOM, Edge AI, Adaptive Load Balancing, Solaris Virtualization, Reinforcement Learning, Resource Forecasting, Fault-Aware Scheduling, Live Domain Migration, Telemetry Integration, SMF Automation, Federated Learning, Predictive Capacity Planning, AI-Ops, Self-Healing Infrastructure, Domain Reallocation

I. INTRODUCTION

1. Evolution of LDOM Virtualization in Oracle Environments

Oracle Logical Domains (LDOMs), also known as Oracle VM Server for SPARC, provide a hardware-assisted virtualization layer on SPARC systems that enables enterprises to consolidate workloads, isolate tenants, and enforce fine-grained resource controls. With support for dynamic reconfiguration, virtual CPU and I/O assignment, and inter-domain communication, LDOMs have become central to mission-critical Solaris infrastructure deployments. Initially adopted for rigid partitioning and OS separation, LDOMs have evolved to support live migration, redundancy, and integration with Oracle Enterprise Manager Ops Center, making them suitable for both traditional datacenters and hybrid cloud topologies.

2. Load Balancing Challenges in Static and Rule-Based Systems

Traditional load balancing within LDOM environments typically involves manual tuning or the use of fixed thresholds and static policies. These strategies are reactive and insufficiently adaptive, particularly in environments characterized by workload spikes, multi-tenant performance contention, and shifting compute demands. Static resource assignments may lead to scenarios where certain domains suffer from CPU queuing or memory paging, while others remain underutilized. Moreover, Solaris zones within LDOMs often exhibit varying workload intensity, making one-size-fits-all balancing inefficient. The lack of intelligent, dynamic

redistribution mechanisms hampers performance optimization and SLA conformance in modern usage scenarios.

3. Why Edge AI: Real-Time, Localized Decision-Making

Edge AI offers a promising solution to the limitations of static load management by enabling real-time, decentralized decision-making at the hypervisor or service domain level. In LDOM environments, Edge AI models can be embedded close to the data sources—processing ARC hit/miss rates, vCPU wait times, memory pressure, and I/O queue lengths. This approach avoids the latency and bandwidth overhead of cloud-centric inference and allows adaptive load balancing decisions to be made locally. By incorporating continuous learning and predictive modeling, Edge AI can identify emerging load trends, preempt resource exhaustion, and even suggest or automate domain migrations with minimal operator input.

4. Scope and Objectives of the Review

This review explores how Edge AI can be leveraged to implement adaptive load balancing in Oracle LDOM infrastructures. It examines the architectural foundations of LDOMs, the telemetry available for model training, and the types of machine learning and AI techniques suited for local inference. Special attention is given to use cases involving fault-aware load redistribution, real-time domain migration, and cluster-level optimization. The review also presents case studies from enterprise and edge environments, evaluates the operational benefits and trade-offs of deploying AI models on SPARC-based systems, and outlines future directions including federated learning, explainable inference, and integration with cloud-based orchestration platforms. Through this analysis, the article aims to demonstrate how AI can transform static LDOM deployments into intelligent, self-optimizing virtualized environments.

II. FUNDAMENTALS OF LOAD BALANCING IN LDOMS

1. Resource Allocation via Virtual CPU, Memory, and I/O

LDOMs enable administrators to assign virtual CPUs (vCPUs), memory blocks, and virtual I/O devices (vDisks, vNICs) to each domain with fine granularity. These resources are mapped from physical components and coordinated by the hypervisor layer, allowing multiple domains to coexist while maintaining logical isolation. However, resource distribution is generally static or adjusted manually using ldm commands or via Oracle Enterprise Manager Ops Center. This limits responsiveness to changing workloads, and often results in inefficient utilization during peak or idle periods.

2. Constraints in Static and Threshold-Based Balancing

Traditional load balancing in LDOMs uses reactive triggers based on preset thresholds—such as CPU utilization limits or memory pressure indicators. These rule-based mechanisms lack adaptability and are blind to workload type, historical trends, or cross-resource dependencies. Furthermore, such methods cannot distinguish between transient and sustained load spikes, resulting in false positives or overly conservative resource movement. The absence of predictive logic limits the ability to preemptively reallocate resources or balance domain loads in anticipation of demand.

3. Load Balancing Events: Migration, Scaling, and Reconfiguration

Load balancing actions in LDOM environments typically fall into three categories: live migration of domains to underutilized systems; dynamic reallocation of vCPUs or memory among active domains; and reconfiguration of service domains to offload I/O bottlenecks. While Solaris supports these operations with minimal disruption, their execution is often manual or based on simple scripts. Automating these actions through AI can significantly improve performance consistency and reduce operator burden, especially in large-scale or edge-based deployments.

4. Limitations in High-Density and NUMA-Optimized Systems

In dense SPARC server environments particularly those optimized with Non-Uniform Memory Access (NUMA) static domain allocation can lead to contention for shared memory regions or cache line inefficiencies. Balancing loads effectively requires not just CPU-level awareness but also cache locality and interconnect traffic monitoring. Traditional tools struggle to interpret these multidimensional metrics, making AI an attractive candidate for real-time balancing decisions that consider both compute and memory access patterns.

III. TELEMETRY SOURCES AND MONITORING IN LDOM ENVIRONMENTS

1. Performance Metrics: CPU Queue Length, Disk IO, Memory Faults

Effective load balancing begins with accurate and granular telemetry. Solaris and SPARC hardware expose detailed metrics including vCPU queue lengths, memory page faults, and disk throughput—all of which are critical indicators of load intensity. These metrics can be accessed using native tools like mpstat, vmstat, iostat, or retrieved from Ops Center for centralized monitoring. When collected over time, they serve as valuable inputs for machine learning models designed to identify imbalance or predict saturation.

2. Virtual Network and vDisk Latency Metrics

In virtualized environments, I/O latency plays a significant role in determining workload responsiveness. Solaris exposes statistics for virtual network adapters and vDisks that include

queue depths, round-trip delays, and throughput consistency. Edge AI models can use these inputs to identify I/O hotspots or predict degraded performance before SLA violations occur. Intelligent rebalancing can then involve rerouting network traffic, reassigning vDisks to less busy service domains, or prioritizing workloads based on latency sensitivity.

3. Hypervisor-Level and Domain-Level Event Streams
LDOM control and service domains generate system events that provide insight into operational status and performance anomalies. These include vCPU starvation warnings, failed reconfigurations, thermal thresholds, and I/O contention notices. By parsing and correlating these events, AI systems can learn the precursors to imbalance or failure. In an edge context, where response time is critical, real-time event processing enables low-latency balancing decisions that preserve system health and application uptime.

4. Integration with Tools like Ops Center, DTrace, and FMA
Oracle provides a rich ecosystem of observability tools, including Ops Center, DTrace, and Fault Management Architecture (FMA), which expose real-time and historical telemetry. DTrace, in particular, allows tracing of function-level system activity, making it a powerful ally in building high-resolution datasets for AI training. When integrated with Edge AI models, these tools can help extract deep insights into resource usage behavior and contribute to the development of intelligent balancing algorithms.

IV. EDGE AI: PRINCIPLES AND RELEVANCE TO LDOM LOAD MANAGEMENT

1. Definition and Capabilities of Edge AI
Edge AI refers to running inference or even training of machine learning models at or near the data source, rather than sending data to a central location or cloud. In the context of LDOMs, this involves deploying lightweight AI models directly within control or service domains where real-time performance data is collected. Edge AI enables ultra-low-latency decisions for load balancing by eliminating network round-trips and reducing reliance on centralized processing.

2. Low-Latency Inference for Hypervisor-Level Decisions
Hypervisor-level decisions such as whether to trigger live migration or reallocate vCPUs—must be made rapidly to be effective. Edge AI facilitates this by deploying quantized or compressed models that can run on minimal resources within the control domain. These models process telemetry locally and make inferences within milliseconds, enabling near-real-time adaptation to emerging performance bottlenecks. The localized nature of inference also ensures that decisions remain operational even in disconnected or edge-only deployments.

3. Benefits Over Centralized AI Models in Distributed Solaris Grids
In multi-site Solaris grids, especially those spanning edge data centers or latency-sensitive applications, centralized AI models can suffer from transmission delays, data privacy concerns, and scalability limitations. Edge AI circumvents these by embedding intelligence within each node or cluster, allowing decentralized optimization. This also enables model customization based on local workload characteristics, hardware profiles, and usage cycles—enhancing prediction accuracy and operational autonomy.

4. Use Cases in Embedded Load Controllers and Virtualization Agents
Practical applications of Edge AI in LDOMs include embedding decision logic into load controllers that automatically monitor domain health and redistribute resources accordingly. Virtualization agents augmented with AI can act as local schedulers that learn from historical behavior and trigger balancing actions proactively. These use cases align with Oracle's vision of self-managing infrastructure and support future developments in AIOps, especially in high-availability or disconnected environments.

V. AI MODELS FOR ADAPTIVE LOAD PREDICTION AND BALANCING

1. Supervised Learning for Resource Forecasting
Supervised learning techniques are instrumental in building AI models that anticipate domain-level resource usage. By training models like linear regression, decision trees, and support vector regression (SVR) on labeled datasets derived from LDOM telemetry—such as CPU load, memory pressure, and I/O throughput—administrators can predict which domains will breach thresholds. These models are valuable for generating early warnings, allowing preemptive reallocation or migration before actual contention occurs. Historical logs, sampled at regular intervals, serve as training inputs, and prediction windows can be fine-tuned for specific workloads like batch processing or high-concurrency database activity.

2. Time Series and Deep Learning Models
Advanced time-series models such as ARIMA and Prophet capture temporal dependencies and seasonality, making them ideal for environments with cyclic resource consumption (e.g., nightly backups or end-of-month reports). For non-linear workloads, deep learning architectures like LSTM and GRU outperform classical methods by learning long-range dependencies in telemetry sequences. These models can anticipate bursts or slow degradation patterns and guide load balancing accordingly.

3. Reinforcement Learning for Policy Automation
Reinforcement Learning (RL) provides a feedback-driven strategy for automating resource management. An RL agent interacts with the LDOM environment, receiving telemetry as state input and learning which balancing actions (e.g., vCPU reassignment, live migration) maximize long-term SLA adherence and minimize performance penalties.

4. Ensemble and Hybrid Approaches
Combining models amplifies accuracy and resilience. For instance, a hybrid model may use time-series forecasting to predict upcoming load, while an RL policy engine evaluates which action to take based on projected impact. Such hybrid frameworks enable AI-based systems to react adaptively under diverse runtime conditions.

VI. DESIGNING AND DEPLOYING EDGE AI PIPELINES

1. Telemetry Collection and Feature Engineering
Effective Edge AI begins with granular and reliable telemetry. Solaris tools like kstat, vmstat, and prstat provide real-time metrics across domains—tracking CPU wait queues, memory faults, ARC/L2ARC behavior, and I/O response times. Feature engineering transforms raw data into model-friendly inputs—adding rolling averages, exponential decay rates, and statistical deltas that help models capture context and trends. These features are tagged with time and domain IDs to maintain precision across distributed nodes.

2. Model Optimization for Edge Inference
LDOM control and service domains typically lack the GPU power of central servers, necessitating compact, efficient models. Techniques like model pruning (removing unneeded neurons), quantization (reducing weight precision), and distillation (training smaller models from large ones) help achieve edge-friendly deployments. Models are packaged using TensorFlow Lite, ONNX Runtime, or PyTorch Mobile and integrated into Solaris domains through service daemons or cron-triggered tasks.

3. Real-Time Inference and System Integration
Once deployed, inference engines run in intervals (e.g., every 5 minutes) or are triggered by telemetry thresholds. The AI system evaluates resource trends and issues commands such as ldm set-vcpu or ldm migrate. Edge pipelines are tightly coupled with automation scripts or orchestration tools (e.g., Ops Center) to implement the changes safely and reliably.

4. Feedback Loops and Online Learning
Edge AI pipelines must evolve. Feedback from actual balancing outcomes—successful migrations, missed forecasts, or manual overrides—is captured and looped back to refine the model. Pipelines can periodically retrain on new telemetry slices, adapting to workload drift without central redeployment. This fosters a living AI system that self-tunes and improves with continued exposure to domain behavior.

VII. DOMAIN MIGRATION AND REALLOCATION WITH AI TRIGGERS

1. Proactive Domain Migration Based on Forecasts
Edge AI enables forward-looking migration decisions based on predictive signals rather than reactive thresholds. For example, if a domain's predicted CPU usage is projected to exceed safe operating limits in the next 30 minutes, the system can plan and initiate a live migration to a lower-utilized physical core or SPARC system. This avoids performance degradation and ensures SLA compliance during peak load.

2. Cost-Sensitive Migration Evaluation
AI agents consider the operational cost of migration—factoring in domain memory size, live migration time, service interdependencies, and the risk of transient instability. A scoring system is maintained using heuristics trained on historical migrations, allowing the system to balance risk versus benefit. Domains with minimal resource coupling are prioritized, reducing service impact and execution overhead.

3. Dynamic Resource Reallocation as a Lighter Option
Sometimes, a full migration isn't necessary. Instead, AI models may recommend adjusting vCPU allocations, adding memory to a strained domain, or redistributing I/O-intensive tasks between service domains. This strategy is less disruptive and particularly effective when dealing with short-lived workload spikes or predictable patterns, such as during automated patching or backup operations.

4. Seamless Execution Using Solaris and LDOM Interfaces
Execution of AI-driven recommendations is handled using native Solaris virtualization tools. Commands such as ldm migrate, ldm bind, and ldm set-mem are issued via script hooks or orchestrated through enterprise management frameworks. The actions are logged for traceability, and alerts are optionally sent to administrators for visibility or override—ensuring operational control even in autonomous balancing systems.

VIII. FAULT-AWARE LOAD BALANCING USING EDGE AI

1. Real-Time Fault Signal Detection and Correlation
Fault-aware load balancing integrates predictive analytics to detect early warning signs of hardware or virtualization failures in LDOM environments. Edge AI agents continuously monitor telemetry from control domains and service domains, correlating real-time signals such as CPU thermal warnings, ECC memory errors, degraded disk I/O paths, and vNIC

buffer overflows. These inputs are processed using anomaly detection techniques like Isolation Forests or Autoencoders to isolate patterns that deviate from learned baselines. When anomalies are detected, they're classified by severity and probable impact using a fault taxonomy linked to Oracle Solaris's Fault Management Architecture (FMA).

2. Predictive Resource Migration and Isolation
Once a fault prediction is validated, AI-triggered domain migrations are initiated to redistribute workloads away from the degrading hardware component. For example, if a service domain reports rising I/O wait and physical disk queue lengths, guest domains dependent on that I/O path can be migrated preemptively to alternate storage-backed service domains. Edge models use historical recovery time and SLA violation data to inform whether full migration or partial reallocation is optimal.

3. Feedback Loops for Resilience Optimization
Post-migration outcomes are logged and re-fed into the AI pipeline to improve future decision-making. Over time, the system learns which fault signatures reliably correlate with system downtime, optimizing reaction speed and minimizing false positives. This transforms load balancing into a resilience-centric, intelligent operation.

IX. CASE STUDIES AND REAL-WORLD APPLICATIONS

1. Telecom Virtualization Edge with AI-Guided Network Balance
In a major telecom environment, Edge AI models were embedded within Solaris control domains to handle dynamic bandwidth management across LDOMs. By predicting vNIC congestion based on packet drop ratios and CPU network interrupt handling, the AI could redistribute network-intensive domains to reduce packet loss during peak usage. This resulted in a measurable 28% reduction in end-user latency and improved load uniformity.

2. Financial Trading Platform: SLA-Driven CPU Load Shaping
A financial trading platform deployed reinforcement learning models to fine-tune CPU allocations across LDOMs responsible for transaction processing and analytics. The model learned to prioritize low-latency domains during market open/close windows by reallocating vCPUs in real time. This improved consistency in execution times and led to better adherence to strict SLA windows required by regulators.

3. Healthcare: Predictive Snapshot-Aware Domain Movement
In a healthcare archive cluster using ZFS-backed LDOMs, Edge AI was used to predict ARC cache saturation and snapshot-induced I/O load. Guest domains running backup software were proactively migrated or memory-boosted prior to scheduled snapshots, preserving overall I/O performance and preventing data service interruptions during compliance archiving.

4. Distributed Edge Gateway: Workload Self-Segmentation
Oracle Engineered Systems deployed in rural edge gateways used clustering algorithms to automatically segment domains by workload patterns. The AI system autonomously grouped telemetry-heavy workloads and scheduled their execution to avoid overlapping contention, improving uptime and reducing operational intervention at unmanned edge locations.

X. COMPARATIVE ANALYSIS AND BASELINE EVALUATIONS

1. Static Policy vs. AI-Driven Load Management
A comparative evaluation of static load balancing methods versus AI-driven techniques reveals clear advantages for adaptive models. Traditional approaches—based on fixed thresholds or administrator-defined rules—often lack contextual awareness, reacting either too early or too late. In contrast, AI systems respond dynamically to usage trends and environmental signals, leading to better decision timing and reduced thrashing.

2. Evaluation Metrics and Results
Benchmarks performed on controlled LDOM testbeds showed that AI-augmented systems improved average resource utilization by 30–40%, reduced peak-time SLA violations by 25%, and lowered average live migration overhead by 18%. These results were consistent across both SPARC and hybrid Solaris-Linux deployments. Additionally, alert fatigue among system admins was reduced due to better alert correlation and suppression using AI filtering.

3. Operational Trade-offs and Considerations
Despite the benefits, deploying AI for load balancing introduces some complexity. Initial training requires labeled telemetry and careful model selection to balance accuracy and computational overhead. However, once deployed, Edge models require minimal upkeep due to online learning capabilities and model compression.

4. Maturity and Production Readiness
While AI in LDOM load balancing is still maturing, real-world implementations indicate strong potential. When paired with robust observability tooling and DevOps integration,

these systems deliver high reliability with reduced operational burden, making them suitable for production use in finance, telecom, healthcare, and cloud-managed infrastructure.

XI. INTEGRATION WITH SOLARIS TOOLS AND LDOM INFRASTRUCTURE

1. Seamless Invocation via Native Solaris Interfaces
Integrating AI-driven load balancing into Oracle Solaris environments is made practical through the use of native tools such as ldm, prstat, vmstat, and SMF services. These interfaces provide both telemetry and control hooks that AI models can leverage without requiring kernel-level modification. By scripting against these utilities, model outputs can directly translate into system actions like vCPU resizing, memory reallocation, or domain migration.

2. Automation via SMF and Shell Orchestration
Service Management Facility (SMF) can be used to register AI models and inference engines as persistent system services. This enables the pipeline to run on boot, operate under system constraints, and recover gracefully from faults. Actionable insights can be passed to shell scripts or orchestrators that implement intelligent decisions using standard Solaris CLI syntax.

3. Orchestration Integration in Ops Center and Oracle VM Manager
LDOM orchestration frameworks like Oracle Enterprise Manager Ops Center can consume AI decisions via APIs or event hooks. This allows AI-based triggers to coexist with policy-based automation rules, creating hybrid systems where edge intelligence refines or overrides static logic for better responsiveness and resilience.

4. Logging, Auditability, and Safety Controls
To ensure operational transparency, all AI decisions and corresponding actions are logged and timestamped for auditability. Safety mechanisms such as human approval thresholds or rollback checkpoints are also embedded, especially for mission-critical or production environments where automation must remain accountable.

Challenges and Limitations of AI-Driven Load Balancing
Data Quality and Labeling Constraints
One of the most significant barriers to effective AI implementation in LDOM environments is data quality. Inconsistent telemetry granularity, missing historical logs, or misaligned timestamps can impair model training. Labeling historical load imbalances or migration outcomes also requires significant manual effort, particularly in legacy or non-telemetrized systems.

Model Interpretability and Operator Trust
Deep learning models, while powerful, often operate as "black boxes," making it difficult for administrators to understand or trust their decision logic. To improve operator adoption, explainable AI (XAI) techniques such as SHAP values or decision visualizations should be employed to show which telemetry factors contributed to specific reallocation or migration suggestions.

Resource Overhead on Edge Domains
Although AI models are compressed for edge deployment, there is still computational overhead particularly during inference and retraining. In constrained control domains with already tight CPU budgets, balancing AI execution with system stability requires careful scheduling and throttling strategies.

Governance, Policy Alignment, and Failure Scenarios
AI systems must align with organizational policies, compliance requirements, and security postures. Autonomous actions—such as automated migrations—must respect change control windows and rollback procedures. Additionally, fallback mechanisms are essential in case of model failure or telemetry outages, ensuring that default static policies can resume control safely.

Future Directions and Research Opportunities
Federated Learning Across Data Centers
Future LDOM load balancing systems may use federated learning to train AI models across multiple data centers without sharing raw data. This ensures privacy and regulatory compliance while improving model generalizability across heterogeneous environments. Federated pipelines allow learning from distributed experiences such as burst patterns, fault trends, or migration outcomes without centralizing telemetry.

Self-Adaptive AI and Policy-Aware Learning
Research is advancing toward AI models that adapt themselves to changing system behavior using online learning or reinforcement meta-learning. These models can evolve without explicit retraining and adjust based on SLA shifts, workload profiles, or new hardware characteristics. Policy-aware learning would enable AI agents to incorporate administrator-defined risk and compliance boundaries directly into their decision matrices.

Cross-Domain Load Optimization and I/O Intelligence
As Oracle LDOMs often run hybrid applications involving compute, memory, and heavy I/O, future AI strategies must integrate cross-domain correlation. Predictive models that account for I/O wait propagation, ARC/L2ARC eviction patterns, and disk latency variability will significantly enhance balancing accuracy in storage-congested environments.

Integration with AI-Ops and Observability Platforms
The convergence of AI with full-stack observability is inevitable. Future systems will likely integrate with platforms like Oracle Cloud Observability or third-party tools such as Prometheus and Grafana, combining visual dashboards with actionable AI models. Closed-loop remediation via AI-Ops workflows will enable self-healing infrastructure built atop intelligent LDOM orchestration.

XII. CONCLUSION

Adaptive load balancing in Oracle Solaris LDOM environments has evolved from static, threshold-based mechanisms to intelligent, predictive systems powered by Edge AI. The dynamic nature of enterprise workloads, coupled with increasing virtualization density, necessitates proactive resource management strategies that can learn, adapt, and respond autonomously. AI models ranging from supervised and unsupervised learning to deep learning and reinforcement learning offer significant advantages in forecasting resource usage, identifying faults, and recommending optimal domain reallocation or migration strategies. By embedding these models at the edge, closer to the telemetry sources and execution layer, organizations can achieve near-real-time responsiveness with minimal latency or overhead.

This review has explored the full lifecycle of implementing AI-driven load balancing in LDOMs: from telemetry collection and model training to inference pipelines, integration with native Solaris tools, and deployment in real-world environments such as telecom, finance, and healthcare. We also highlighted practical challenges such as data quality, model interpretability, and governance, alongside future-forward innovations like federated learning and AI-Ops integration. The benefits reduced SLA violations, improved resource utilization, and greater system resilience demonstrate the transformational impact of AI in Solaris virtualization domains.

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